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Unconventional Shale Gas Development, Risk Perceptions, and Averting Behavior: Evidence from Bottled Water Purchases

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Unconventional Shale Gas Development, Risk Perceptions, and Averting Behavior: Evidence from Bottled Water Purchases[*]

Technological innovation has made extraction of natural gas from deep shale formations economically viable. While unconventional shale gas development is seen as an economic benefit, concerns have been raised about the environmental and health risks associated with the extraction process. We combine GIS data on unconventional shale gas development in Pennsylvania and Ohio with household data on bottled water purchases to assess the impact that perceived risks to drinking water from unconventional shale development have had on household well-being using a treatment effects design. In our preferred triple difference models with time-varying treatment effects, we find per-household averting expenditure in 2010 ranges from $10.74 in our full sample specification to $15.64 when omitting urban counties more likely to contain public water supplies. Converting the sample-average averting expenditure of $10.74 to an annual expenditure for the entire impacted population implies an averting expenditure in Pennsylvania shale counties exceeding $19 million for the year 2010.

Keywords: Hydraulic Fracturing, Risk, Averting Behavior, Water

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I. Introduction

Advances in technology have made extraction of natural gas from deep geological shale formations economically viable.[1] The dramatic increase in gas production from these unconventional sources is viewed by many as a significant benefit to the U.S. economy although there is considerable concern among the public about potential environmental damages, including drinking-water safety.[2] In this paper, we develop a series of difference-in-difference (DD) and difference-in-difference-in-difference (DDD), or triple difference, treatment effects models and apply them to data on yearly household bottled water purchases from Pennsylvania and Ohio to examine the level of averting expenditure due to perceived risks to drinking water. Triple difference estimates of averting behavior using scanner data on households' yearly bottled water purchases for the years 2005-2010 reveal averting expenditure in 2010 that ranges from $10.74 in our full-sample specification to $15.64 after omitting urban counties that are more likely to contain public water supplies. Converting the sample-average averting expenditure value from our full-sample model to a population wide measure reveals total averting expenditure of over $19 million for households in Pennsylvania's shale-gas counties in 2010 alone; a similar conversion using the non-urban sample reveals a total expenditure value of almost $20 million. These results are robust to a wide range of specifications. Our results confirm the intuition that averting expenditure should increase over time as shale activity increases, increase in areas experiencing greater levels of shale development, and increase in rural counties where households are more likely get their drinking water from private wells.

This paper sheds new light on one of the most contentious debates surrounding increased unconventional gas development – that new shale gas extraction techniques will lead to the contamination of local ground and surface water supplies. Water quality concerns arise during the fracturing process when large amounts of water, used to force open fissures in shale formations, are returned to the surface (Kuwayama et al., 2013). This waste water routinely

[1] The rate of natural gas production from shale has risen over the last decade in the U.S. In 2005, gas from unconventional sources accounted for only 4.1 percent of total U.S. production; by 2010 it had reached 23.1 percent (Wang and Krupnick, 2013).
[2] The potential for methane leakage (Howarth et al., 2011; Burnham et al., 2012), air pollution (Kargbo et al., 2010; Schmidt, 2011), water pollution (Osborn et al., 2011; Olmstead et al., 2013; Wilson and Van Briesen, 2013; Wilson et al, 2013), and local road congestion (Baily, 2010; Considine et al., 2011) are the most frequently cited negative side effects.

contains high levels of brine, heavy metals, and other potentially toxic chemicals used during the fracturing process; it can also contain methane. Given that the well bore and casing pass through underground water sources, concerns have been raised about the potential for fracking water to migrate from shale gas wells to drinking water wells (Osborn et al., 2011; Saiers and Barth, 2012; Warner et al., 2012; Darrah et al., 2014).

In addition to threats to groundwater, other research has addressed the potential for shale gas development to impact surface water supplies. Following production, drilling companies must dispose of the waste water from the fracturing process. Two of the most common disposal methods in the Marcellus region during the 2005-2010 period were underground injection (into Class II injection wells) and shipment to local wastewater treatment facilities. In the latter case, the ability of local facilities to remove fracking contaminants from waste water before it was discharged into local streams and rivers raised the specter of surface water contamination as many local facilities were ill-equipped to handle the residual chemicals in the fracking water.[3] In the first systematic study of this threat, Olmstead et al. (2013) used spatially explicit water quality data from Pennsylvania and looked at the impact of the release of treated shale gas waste by permitted facilities on observed downstream concentrations of chloride. The authors found that the treatment of shale gas waste by wastewater treatment facilities in a watershed raised downstream chloride levels as a result of excess brine remaining in the discharge water. In addition, they found that runoff from the actual drilling sites raises the level of total suspended solids in waterways downstream from the well site.

Whether water contamination occurs in any systematic fashion is a hotly debated topic (Osborn et al., 2011; Saiers and Barth, 2012; Warner et al., 2012; Darrah et al., 2014). Nevertheless, even the perception of risk can have an impact on human well-being insofar as it impacts the choices people make to reduce these threats. Averting behavior is likely as households attempt to protect themselves when faced with both realized and perceived environmental or health risks. The key challenge in identifying this change in behavior is establishing a baseline for which to measure the magnitude of altered behavior. In the case of

[3] During our study period local wastewater treatment facilities handled significant amounts of waste water from Marcellus shale gas development. However, since 2010-2011 this trend has changed and now most of that water is recycled with very little going to local facilities. This is not the case with the fracturing of other shale formations, such as the Utica. We thank a reviewer for pointing this out.

drinking water contamination, a natural substitute for drinking water is prepackaged water, which is readily measureable through scanner data. Changes in purchasing patterns, if observed and driven by exogenous forces, allow us to gauge the pathways by which risks translate into changes in well-being.[4]

One way to establish a baseline, and a general understanding of how the relationship between Marcellus shale gas development and perceived water-related risks may have changed over time, is to use Google Trends and plot search data related to shale gas development. In Figure 1, we have plotted two monthly data series for our study period (2005-2010) obtained from Google Trends' searches of "Shale" (top portion of Figure 1) and "Fracking" (bottom portion of Figure 1). Both the top and bottom panels include individual data series from Pennsylvania and Ohio, plotted in relative terms. From this figure, it is clear that both search terms show much more search activity in Pennsylvania than in Ohio, and that online interest significantly increased in the last two years of our study period, which is what we would expect given that this is when most of the wells and drilling activity took place in Pennsylvania.

While these search terms are broad and likely include both positive and negative search motivations, they nevertheless suggest a pattern of online search activity in Pennsylvania related to shale and fracking during our study period. While there is some search activity in Ohio, relative to Pennsylvania the magnitude of this activity is small. Thus, Figure 1 provides some anecdotal evidence that the general population was interested in shale-related issues, both positive and negative, and that this interest was significantly heightened in Pennsylvania (our treatment state) relative to Ohio (our control state), especially in the latter years of our data.

A number of recent papers using data on well locations and home sales have looked at the impact of shale gas development on changes in property values (Boxall et al., 2005; Muehlenbachs et al., 2013; Klaiber and Gopalakrishnan, 2014; Muehlenbachs et al., 2014). These papers find that, while the effect of shale gas wells on property values varies with the location and type of property, there is a negative capitalization effect for properties in close proximity to wells without access to public water. Specifically, using data from Pennsylvania

[4] Other possible averting behaviors could include installing water filters or arranging for regular water deliveries. Even the sale of one's house can be seen as a form of averting behavior. If the threat of drinking water contamination is large enough to induce some households to sell their home and resort, then the simple change in capitalization, while not a measure of willingness to pay, can be reframed as another lower-bound measure of averting behavior.

and New York, Muehlenbachs et al. (2014) estimate a treatment effects model similar to ours and find that properties on well water and located 1.5 km or closer to a shale gas well see their property values drop, on average, by between 10% and 22.4%. To the extent that changes in property values reflect changes in risk perceptions, these findings suggest that shale gas development has a negative impact on economic well-being for nearby residents.

While home sales and changes in property values provide one method to gauge the reaction of households to changes in the risks associated with shale gas development, it is also likely that a household will alter its behavior in a more subtle way. A common method employed by households to guard against threats from contamination is through changes in the types of goods and services they purchase. In the case of threats to private water supplies, households typically search for alternative sources of water.

Potable water is a fundamental input into most household production functions. It is expected that when the threat of contamination to a household's water supply increases purchases of bottled water will increase. If the researcher is able to observe these changes, then increases in bottled water purchases provide an estimate of the economic benefits of policies designed to reduce the threat to drinking water supplies. A number of recent papers have applied a similar logic and examined threats related to mercury (Shimshack et al., 2007), water quality violations and advisories (Abdalla et al., 1992; Graff Zivin et al., 2011), hurricanes (Shimshack and Beatty, 2014), and risk perceptions related to water contamination (Jakus et al., 2009).[5]

Our paper builds on this previous work and examines how yearly household purchases of bottled water have changed as unconventional shale gas development has increased in recent years. The focus of our research is on the impact that positive levels of shale gas development, at the county level, have had on household purchasing decisions. Since we do not directly observe actual water-quality violations, and our data do not allow us to link each household to a specific well[6], we classify risks as perceived and assume that changes in household decision making are directly associated with the potential threat of water contamination related to increases in the intensity of shale gas development at the county level. The existing research on possible shale

[5] This entire line of reasoning follows from the idea that bottled water is safer and cleaner than the alternative. However, if people are concerned that the filtering process for bottled water makes it less safe, then this could dampen the impact from bottled-water purchases.
[6] While we have household-level observations on bottled-water purchases, the lowest spatial resolution in the data is at the county level.

well contamination of both private well water and public water supplies suggests that households across a large area are likely to perceive these types of risk. Exploiting spatial and temporal variation in well activity and purchasing patterns, our data and methodology enable us to identify changes in these risk perceptions and how these changes impact household purchases of bottled water.

To evaluate the impact that unconventional shale gas activity has had on household bottled water purchases, we estimate variants of two separate treatment effects models (DD and DDD models). To estimate each model, we use data on household bottled water purchases for the years 2005-2010 defining the pre-treatment period as 2005 and 2006 and the post-treatment period as 2007-2010. These periods are chosen both due to data availability and because they bound the rapid expansion of unconventional shale-gas development in the Marcellus region of Pennsylvania in 2007. In each model, we hypothesize that a binary treatment effect, as defined by a positive level of unconventional well activity in a given county, impacts the perceived risks of households living in shale gas counties. For the DD models, we compare shale active counties in Pennsylvania with similar counties in Ohio that had not yet experienced shale activity as of 2010, but have experienced this activity as of 2015. For the DDD models, we add information on non-shale counties in both Pennsylvania and Ohio to control for potentially unobserved time-varying trends in water expenditure across the predominately rural and mountainous shale counties and the more urban, less mountainous non-shale counties in each state. The results from a wide variety of model specifications reveal that households in shale active (treatment) counties increase yearly bottled water purchases relative to control counties.

The remainder of the paper proceeds as follows. In the next section, we provide a brief discussion of the theory of averting behavior and describe the empirical framework used to construct our lower-bound welfare estimates. Section III describes the data used in the model; Section IV presents our main results and series of robustness checks; and Section V concludes.

II. Theory and Estimation

Averting behavior arises from a household optimization problem where each household chooses inputs into a production function in order to produce optimal outcomes for the members of the household. In cases where the household is exposed to potentially toxic or harmful substances, the household engages in defensive expenditures designed to protect itself from these risks

(Bartik, 1988). In some cases the pathway from toxic exposure to a particular health or environmental outcome is explicit with each household choosing an optimal level of environmental quality based on its preferences. In other cases, however, the actual demand function for environmental quality is not available.[7]

In our data, we do not observe a direct connection between changes in water quality and an increase in shale gas development. Moreover, the actual relationship between water contamination and unconventional shale gas development is largely uncertain, which makes the specification of a theoretical demand function for environmental quality problematic. As a result, we follow previous research (Jakus et al., 2009; Graff Zivin et al., 2011) and assume that risks from shale gas development are implicitly related to the existence of well activity at the county level – i.e., we assume that a households' risk perceptions and their decision to undertake defensive expenditures are affected by being located in a county that is currently subject to unconventional shale gas development.

Based on the theory in Bartik (1988), our goal is to generate an estimate of the non-market costs of increased risk perceptions from shale gas development. Ideally, this estimate would include all defensive measures (bottled water purchases, household water filtration systems, on-site water tanks, etc.), which households take to avert risks from shale gas activity. Our data, however, only include households' purchases of bottled water, so we use these data for our measure of household averting expenditure with the caveat that they only provide a lower bound on the potential measures households take to avoid potential risks associated with shale gas development.

To empirically implement our model of averting expenditure, we assign each household a binary level of risk exposure, or treatment, from unconventional well drilling based on whether the household is located in a county with a positive level of unconventional shale gas development. We then use this county-level treatment to estimate our DD and DDD models based on these county-level treatments. We include a large set of time-varying demographic controls, including income, age, and education status to account for potential factors driving the

[7] In most cases the researcher only observes the final choices the household makes or expenditures before and after a change in exposure and not the explicit pathway between changes in purchases or expenditure and how those impact the actual choice of environmental quality by the household.

household's purchase decisions related to potential shale gas risk.[8] We address the issue of potentially unobserved household attributes in all of our models by including time-averages of our independent variables to control for household-level unobservables (Mundlak, 1978).

In the first set of treatment effects models, we use household purchase data from Pennsylvania and Ohio in counties that have experienced shale activity as of 2015 to define treatment and controls. As our data spans the years 2005-2010, we define control counties in Ohio as those that had not yet experienced shale activity by 2010, but have as of 2015. Treatment counties are defined as those in Pennsylvania that experienced shale activity by the end of our data in 2010. Using this division of counties into treatment and control, the empirical specification for our DD model is given by

$$y_{it} = \delta_1 PA + \delta_2 PAPost2006 + \beta x_{it} + h_i + d_t + u_{it}, \quad (1)$$

where y_{it} is yearly bottled water expenditure by household i, x_{it} is a vector of demographic characteristics for the household, h_i are means of household demographics, d_t are year dummy variables, and PA is an indicator for shale gas (treatment) counties in Pennsylvania, which captures possible differences between the treatment and control groups prior to treatment. To form our difference-in-difference estimator, we include an interaction between an indicator for the post-treatment period (2007-2010), which captures aggregate changes in household bottled water purchases that are unrelated to the treatment, and an indicator variable for Pennsylvania, which are the treatment counties in the DD model. The coefficient, δ_2, which captures this interaction between the Pennsylvania treatment group and the post-treatment time period, represents our DD treatment effect estimate.

In our second set of specifications, we extend the DD model in Equation (1) to account for potentially time-varying, non-rural unobservables that could bias our DD results. While the rural and mountainous areas of Ohio and Pennsylvania are very similar in their demographic composition and pre-treatment purchase trends (see below) and thus provide good treatment and control comparisons in our DD specifications, they are quite different from the more urban and

[8] In addition to changing household composition and aging of households, the head of household also changes over time as households dissolve or expand resulting in potentially different racial compositions as well as educational attainment.

agricultural areas of the rest of each state. As a result, it is possible that other state-specific, non-rural changes in water consumption, un-related to shale gas development, but occurring simultaneously with its development, could impact our DD results. To account for this, we use the counties in each state that are not in shale areas as an additional set of controls to form a third difference. These counties serve as an additional control to account for state-level and non-rural unobservables and achieve the third difference in our DDD models. The spatial distribution of the four groups of counties used in our DD and DDD models are shown in Figure 1.

Using data from the entirety of Ohio and Pennsylvania, we estimate a series of DDD models given by

$$\begin{aligned} y_{it} = \delta_1 HasWell + \delta_2 HasWellPost2006 + \delta_3 PA + \delta_4 PAPost2006 \\ + \delta_5 PAHasWell + \delta_6 PAHasWellPost2006 + \beta x_{it} + h_i + d_t \\ + u_{it}, \end{aligned} \tag{2}$$

where the new variable, $HasWell,$ is an indicator for shale counties in Ohio and Pennsylvania, PA is an indicator for counties in Pennsylvania, and $PAHasWell$, $HasWellPost2006$, and $PAPost2006$ are formed by additional interactions. Our key treatment effect variable is obtained by an interaction between the dummy variable for well counties, the post-treatment period dummy, and a state-level indicator for Pennsylvania. The coefficient on this term, δ_6, represents our DDD estimate.

Finally, we extend the DDD model above to examine whether the impact of well-drilling activity changed over time as unconventional shale gas exploration became more widespread. While unconventional shale gas development started in 2007 in Pennsylvania, the majority of the wells that were drilled during our study period occurred in 2009 and 2010.[9] To control for the potentially positive association between risk perceptions and the expansion of activity across our study area, we interact each of our triple-difference treatment variables with a set of time fixed effects for 2006-2010 to estimate the impact that increased well activity in Pennsylvania had on household-level defensive expenditures – i.e., the treatment counties stay constant and the impact of increased drilling activity is identified through changes in county-level intensity over time

[9] It is also evident from Figure 1 that concerns over shale and fracking followed a similar trend.

relative to the base year of 2005 (Yearly DDD). This time-varying treatment allows us to identify the effect that increased drilling has had on household risk perceptions and is captured by replacing the treatment effect term in Equation (2) with a series of time-varying effects given by

$$\sum_{t=2006}^{T=2010} \delta_{6t} * d_t * PA * HasWell. \tag{3}$$

We also conduct a wide range of robustness tests using specifications designed to examine the role of spatial and temporal heterogeneity in treatment effects. In particular, we examine whether spatially driven heterogeneity in treatment results in different levels of defensive expenditure. To address this, we separate the treatment effect into three distinct treatments based on the total number of wells drilled in each county. We would expect an increase in the number of wells drilled in a given county to result in higher averting expenditure as households in these counties are more likely to live near an active well and thus more likely to perceive changes to their risk status. We estimate both the Yearly DDD model and DDD model with different treatment effects based on drilling intensity using the full dataset and a reduced data set where we drop all metro counties. Omitting metro counties allows us to examine whether more rural counties, likely more reliant on private well water as opposed to public water supplies, experience a differential level of averting behavior relative to the entire sample of counties. Finally, we conduct a series of robustness checks aimed at controlling for income effects in shale-gas counties, spillover effects between treatment and control counties, and price effects associated with potential changes in the price of bottled water during our study period.

III. Data

The data used in estimating our models come from several different sources. The shale-well data for Pennsylvania come from the Pennsylvania Department of Environmental Protection SPUD reports. These data contain information of the number of drilling permits issued and the exact location of the well sites in the state from 2007-2010. (The location of all wells drilled in Pennsylvania from 2007-2010 are shown in Figure 2.) Similarly, we obtain location data on well activity in Ohio from the Ohio Department of Environmental Protection. Using these data, we attach each well to a specific county and use county-level well counts to create the treatment and control variables in our empirical models.

Our data on household bottled water purchases come from the Nielsen Corporation's consumer HomeScan panel data set. These data record all food and beverage transactions for a sample of U.S. households in each year from 2005-2010.[10] We chose the years 2005-2010 based on the size of the sample, its geographic coverage, and, most importantly, the ability of the data to bound the start of unconventional shale gas development in the state of Pennsylvania. HomeScan data are available before 2005 and after 2010, but the early years for these data are significantly limited in size and geographic scope limiting their ability to capture rural households; the latter years overlap with the start of drilling in Ohio limiting their use in our DD and DDD models. To create our yearly bottled water data, we identify all households from the HomeScan data that are located in either Pennsylvania or Ohio. We then sum all bottled water expenditures made by each household in a given year, stack these data over time, and merge the data with yearly household demographic characteristics based on a unique household ID. Finally, we combine this information with yearly well data using a county ID variable for each household.

The HomeScan data contain not only information on household purchases, but also a large set of demographic characteristics including household size, income, education level, and age. These demographic characteristics are time-varying as households fill out updated information each year. The demographic variables used in our treatment effects models are shown in Table 1. While the HomeScan data are designed to provide a representative sample of U.S. households and many households appear in the data in more than one year, these data do not represent a traditional panel data set as some households enter and exit the data set during our study period. For example, about 20% of households appear only once during our 6-year study period and 25% of households appear in all six years. To estimate the DD and DDD models in this paper, we drop all households that appear only once and use data for households with two or more observations, which allows us to include time-averaged household variables in each model.

[10] Households in the HomeScan data are provided a scanning device and use it to scan all food and beverage purchases made by the household in a given year. These data are transmitted to Nielsen who aggregate the data and sell them to vendors. We obtained these data via a cooperative agreement between Penn State University and Kilt's Marketing Center at the University of Chicago.

After excluding these households, our final data set contains 27,544 observations across 7,120 households for the years 2005-2010 in Pennsylvania and Ohio; the counts of households across all of the different sets of treatment and control groups are shown in Table 1.

To provide an additional statistical comparison between the demographic controls variables and how these change across the different treatment and control groups, the final two columns of Table 1 show the coefficient values and indicators for statistical significance from a set of regressions run using the individual demographic controls and the DD and DDD treatment effects variables from Equations (1) and (2). We estimate the DD and DDD treatment effects for the continuous variables using a standard OLS model, and we estimate binary variables using a probit model. For the DD results, we find that income, age, and race (black) are significant; for the DDD model only age and race (other) are significant. Overall, the results from these models suggest that changing demographics are unlikely to be a major driver of bottled water expenditure and suggest that our pre-treatment trends in demographics are quite consistent across treated and control groups of households.

To provide additional context for the HomeScan data and its representation of the populations of households in Ohio and Pennsylvania, in Table 2 we compare a number of the variables from our purchase data with variables from the Census data (2008-2012) for Ohio and Pennsylvania. While the HomeScan data appear to be more heavily weighted towards higher educated households than the census, for most of the variables the HomeScan and Census data are very similar, which suggests that they provide an adequate representation of households in our study region. When interpreting our results, if more highly educated households are potentially more responsive to perceived water quality risks, the slight difference in demographics between HomeScan and Census could suggest that our estimates represent slightly elevated levels of averting expenditure compared to the overall Census population.

IV. Results

Difference-in-Differences

One of the key identifying assumptions in any DD model is that treatment and control groups exhibit similar trends in the dependent variable prior to any intervention or change in policy. For our DD model, this implies that average household expenditure in 2005 and 2006 for shale gas counties in Pennsylvania and Ohio follow a similar trend. The absolute values of these average values do not need to be the same, but the trends in average total bottled water expenditure for the pre-treatment years need to follow a similar path.

To provide motivation for our DD econometric estimates, Figure 3 displays the regression lines associated with bi-annual average household expenditure data for well counties in Pennsylvania and Ohio in the pre-treatment period (2005 and 2006) and post-treament period (2007-2010). From this figure, it is clear that the trend in bottled water expenditure, while increasing, is largely the same between Pennsylvania well counties and our control group of Ohio well counties in the pre-treatment period. However, after the onset of shale activity in 2007 we see a significant deviation in trends across well counties in Pennsylvania and Ohio. While all areas experience slight declines during this period, likely due to the recession, the rate of decline in Pennsylvania well counties is much more muted than the declines in the control counties. In fact, in year 2008 the control county line actually declines at a fast enough rate relative to our treatment counties that it crosses and remains below the level of expenditure in shale treated counties throughout the remainder of our study period.

Table 3 provides a numerical summary of average annual expenditure across time that largely mimics the results in Figure 3. Comparing expenditures for treatment and control counties, we see a much more substantial increase in county level expenditure in treated counties in Pennsylvania than control counties after the onset of shale activity. The per-household expenditure increases by 75% in treated well counties in Pennsylvania and actually decreases by 12% in control well counties in Ohio.

The results from three DD models are shown in Table 4 that correspond to Equation (1). The standard errors are robust and clustered at the county-by-year level.[11] Each of these models recovers a single estimate of the impact of shale gas activity on bottled water purchases. The first set of results presents a baseline model that omits household demographics; the second model adds a wide range of household demographic control variables contained within the Nielsen dataset; and the final column includes a full set of household demographic as well as household means to control for unobservable household characteristics. Across all three models, the impact

[11] The standard errors in all models are clustered at the count-by-year level (two-way). We also estimated the models clustering at the county level and obtained similar results. We thank an anonymous reviewer for pointing this out.

of shale activity on bottled water expenditure ranges from a high of $10.10 in model 1 to a low of $7.85 in model 3. In all cases this result is significant at the 95% level or above.

Difference-in-Difference-in-Differences

One concern with using DD models estimated with data from only shale-gas counties, to draw conclusions about averting behavior from bottled water purchases, is that these counties are largely rural and mountainous and quite different from the non-shale, urban and agricultural counties in the remainder of each state. This is partially evident from the group-specific demographic variables in Table 1 with lower incomes and fewer college graduates in well counties. Moreover, it is possible that bottled water purchases within well counties in each state may be systematically different due to changes in income, wealth, or other state-level unobservables not accounted for using treatment and control groups from different states. A more robust alternative to the DD model would include all non-well treatment and control counties from Pennsylvania and Ohio and estimate a DDD model to account for any time-varying, state-level, urban and agricultural unobservables.

Once again, one requirement for the implementation of our DDD model is that the trends in the treatment and control groups in the well and non-well counties follow similar trends – i.e., the treatment and control groups for well counties follow a similar pre-treatment trend and treatment and control groups for non-well counties do the same. In Figure 4, we extend the results from Figure 3 to include the plots of average total bi-annual expenditure for each of the four groups in the DDD model. We can see that the treatment and control group for the non-well counties follow a similar trend in the pre-treatment period; the results for the well counties are the same as Figure 3. For the non-well counties the paths are roughly similar throughout. The full set of yearly average expenditure results are shown in Table 3.

Table 5 presents the empirical estimates from our DDD model in Equation 2. As was the case with Table 4, the first set of results presents a baseline model that omits household demographics; the second model adds household demographic controls; and the final column includes household means to control for unobservable household characteristics. The results from Table 5 suggest a limited role for unobservables that could potentially bias our prior results. The estimated treatment effects from the DDD model range from $9.02 to $7.85, which are largely consistent with the range in Table 4. However, to maintain consistency and robustness throughout the remainder of the paper we will continue to report estimates using our preferred DDD model.

In Table 6, we examine the role of spatial heterogeneity among rural and urban water users by omitting metropolitan counties from our analysis. For each of the models in Table 6, we estimate our DDD model after dropping observations for the city center counties of Cincinnati, Cleveland, Columbus, Philadelphia, and Pittsburgh. Compared to the full-sample results in Table 5, the results in Table 6 show that isolating averting expenditure to largely non-urban, rural households results in an increase in average total expenditure. Averting expenditure from these models ranges from $10.88 to $9.58. This result likely follows from the fact that a more-rural sample of households is more likely to rely on groundwater as their primary water source and thus perceive greater risks due compared to more urban households.

The rapid expansion of shale activity that occurred in Pennsylvania from 2007-2010 was not evenly distributed across counties (see Figure 2). Thus, it is likely that risk perceptions, in the form of increased willingness to pay for safety, were positively associated with increased drilling activity. It is also unlikely that the risk to drinking water was perceived uniformly across households located on private well and public water supplies. Extending the DDD models from Tables 5 and 6, we expect that averting expenditures should be increasing in the level of shale gas activity occurring in a given county. We test this with two additional DDD specifications. We divide our treatment effects variable based on the number of shale gas wells drilled in each county in Pennsylvania to create three separate treatment effects variables with cutoffs at 35 and 135 wells based on the 50th and 75th percentile in the raw well count data. Using the full data set, we report these findings in Table 7 and find that as the level of shale activity increases households averting expenditure increases from $7.46 to $10.00 across the three categories of well intensity. In addition, we find that in a model that omits metro counties averting expenditure increases further and results range from $9.16 to $11.30 across the same intensity categories. These results confirm the hypothesis that rural households exhibit a greater degree of averting expenditure compared to the overall population.

In Table 8, we extend our DDD specification to examine how the impact of increased well activity has changed averting expenditure over time. Following Equation (3), we interact a dummy variable for Pennsylvania with a well county indicator and a set of time dummies to generate time-varying treatment effects. The inclusion of time-varying treatment effects is motivated by the rapid increase in shale gas exploration that occurred during our study period, most especially in 2009 and 2010. As we observed in Figure 1, the Google Trends data suggests that residents of Pennsylvania became increasingly interested in shale and fracking issues in 2009 and 2010. If this interest is at all related to concerns about water quality, then we could expect to see higher average expenditure values in the final years of our data.

The results in Table 8 confirm this trend. We find that households in shale gas counties increase their purchases of bottled water relative to households in control counties. While the coefficient values on the time-varying treatment effects variables are positive from 2007-2010, only the values in 2009 and 2010 are statistically significant. Moreover, the values in 2009 and 2010 are much larger than in the early period when well activity was less widespread. The results in the first column of Table 8 reveal that households located in shale counties in Pennsylvania increased their yearly bottled water purchases by $7.30 and $10.74 in the years 2009 and 2010, respectively. After dropping metro counties in the second column of results, averting expenditure increased to $10.71 and $15.64, respectively. These results provide further evidence of the role of increasing shale activity driving averting expenditure both spatially and over time as activity increased.

Additional Robustness

The results from our DD and DDD models demonstrate a robust and consistent result – specifically that the existence of Marcellus shale gas exploration in Pennsylvania during our study period led to an increase in yearly household bottled water expenditure. Moreover, based on theory and trends found in online data searches it is likely that this resulted from increased perceived risks from ground and surface water contamination. However, it is still possible other factors, not accounted for in the aforementioned models, could be biasing our results. In this section, we provide a series of additional robustness checks aimed at controlling for some of these additional factors.

In Table 9, we estimate two additional variants of our time-varying DDD models. In the first column, we drop all non-well counties in Pennsylvania and Ohio that share a border with shale counties in Pennsylvania; in the second column, we drop both border counties and metro counties. The exclusion of counties that share a border with well counties in Pennsylvania eliminates the potential for spillover effects to impact our averting behavior estimates. Spillover effects may occur if residents in counties surrounding shale activity perceive risks of water contamination and respond to those risks through increased bottled water expenditure despite having no well activity in their counties. The results for these specifications largely mirror our previous findings with averting expenditure significant in years 2009 and 2010 and ranging between $10.11 and $13.51 in the full model omitting only border counties and a slightly higher averting expenditure of $13.34 and $18.36 in the model that also omits metro counties.[12]

While all our previous results focus on overall expenditure consistent with the theory discussed in Section II (Bartik, 1988), if shale counties experienced different trends in bottled water prices over time, compared with non-shale counties, it would be possible that these price changes are at least partially explaining our findings of increased expenditure. To gauge these potential price effects, Table 10 presents results based our yearly DDD model, but focuses exclusively on water volume, rather than overall expenditure, while controlling for the price per ounce of water in each year. The results from this model suggest that changes in prices are not the underlying driver of our findings. In fact, we find similar significance in years 2009 and 2010, which, when converted to averting expenditure using the price per ounce of water, are actually slightly higher than our previous findings. For the full model, we find a 2010 averting expenditure value of $11.46, which increases to $17.50 after omitting metro counties.[13]

We also examine the potential that income effects associated with shale activity were responsible for the increases in expenditure on bottled water, which is presumably a normal good and would command a greater expenditure if incomes were to rise. To examine this, we use data

[12] One additional concern is whether households leave, or sort out of, treatment counties after the onset of drilling, which would lead to sample attrition and nonrandom sampling in treatment counties. To test for this effect, we again estimate our border model (dropping border and metro counties), but with two additional restrictions: (1) we keep only households in treatment counties that show up in the data both before and after the start of drilling and (2) we keep only households in treatment counties that show up in the data in every time period. We have included these results in the Appendix, Table A1. We further test for sorting, we estimate a Probit model for a household's presence in the sample taking a value of 1 if present and zero if absent. The sample includes a balanced (squared) panel dataset of all households observed in the pre-treatment time period. Results indicate no systematic attrition in treated counties and are shown in Table A2.

[13] We also looked at whether sales of water in treatment counties were more often on sale in the years following the onset of drilling and did not find any indication that this was the case. A table of total sales and proportion of sales on promotion by year and treatment group is shown in the Appendix, Table A3.

on non-beverage normal goods and estimate our yearly DDD treatment effects models using a variety of food categories. In Table 11, we estimate the model using the full sample, and in Table 12 we estimate it after excluding all metro counties. We find virtually no statistically significant treatment effects in the years 2009 and 2010 across all 5 food categories. In specifications with significant treatment effects, the results indicate a decrease in expenditure rather than an increase, which is the opposite of what one would expect if income effects were driving our findings. Overall, these findings suggest that unobserved income effects are unlikely to be driving the increased expenditures we observe for bottled water.

Our final set of results directly addresses realized risks in the Pittsburgh region using data from Allegheny and Washington Counties on Safe Drinking Water Act (SDWA) violations obtained from the EPA. There was public concern in the Pittsburgh region over potential contamination from total trihalomethanes (TTHMs), which are byproducts produced by using chlorine to treat wastewater in the presence of brine (States et al., 2013). In 2010, the Pittsburgh, PA water and sewer authority experienced increases in TTHMs coinciding with a time period in which Pennsylvania permitted shale drillers to dispose of wastewater in local municipal treatment plants that were likely unable to fully remove dissolved solids contained in the wastewater. This led to concerns that this disposal method could potentially be related to the increase in TTHMs found in the drinking water for Pittsburgh and eventually led Pennsylvania to stop this form of wastewater disposal (Abdalla et al., 2012). While we cannot directly link these violations to shale activity, it nevertheless enables us to provide a per violation measure of increased bottled water purchases associated with actual risks which were required by law to be communicated to residents following their discovery.

We are limited in our ability to directly determine which Nieslen households experienced notifications of SDWA violations as we only observe Nielsen households at a county level where multiple water providers operate. As a result, we have narrowed our focus to the Pittsburgh region including Allegheny County, PA and Washington County, PA as we are more likely to observe Nielsen households on public water in these highly urban counties. We obtained, from the EPA, a measure of all community water system violations associated with TTHMs. Using these data, we regress yearly household bottled water expenditure for household in these counties on a count of the number of yearly violations in each county and on a set of demographic controls, county fixed effects, year fixed effects, and demographic means. Our data on SDWA

TTHM violations reveals that violations occurred in this region each year from 2005 through 2010. This patterns reflects the fact that TTHM violations are likely associated with a wide range of industrial activity and not simply shale wastewater disposal. However, violations across all water providers did increase over this time period from 7 violations in 2005 to a high of 22 violations in 2008 before decreasing to 16 and 8 TTHM violations in 2009 and 2010, respectively.

While not directly comparable to our measure of shale related risks due to the different treatment effects – actual violations vs. presence and/or quantity of shale activity – examining realized risks provides direct evidence of averting expenditure and establishes that expenditure responses to water risks were occurring in our study region during this period. Estimation results in Table 13 show that households do respond to actual risks with the marginal increase in bottled water expenditure increasing by $2.24 for each additional SDWA TTHM violation. We expect that this measure is a lower bound due to the inability of the data to directly link Nielsen households to water providers. Nevertheless, this provides direct evidence that households did respond to drinking water risks through increased averting expenditure.

V. Discussion and Conclusions

This paper estimates a wide range of DD and DDD models to recover estimates of the averting expenditure caused by increased unconventional shale gas activity in Pennsylvania. Our results reveal a large, robust increase in averting expenditure associated with shale gas activity that has been overlooked in much of the existing research on potential environmental impacts of shale development and is not currently addressed in existing policy. While efforts to impose severance taxes and establish environmental contingency funds are widespread, these monetary forms of compensation at best flow to local authorities and in many cases are simply held for contingency plans.

Table 14 provides a summary of the implied averting expenditure in each of our specifications when multiplied by the relevant impacted population of households in Pennsylvania experiencing shale gas activity as of 2010. In our preferred DDD models with time-varying treatment effects, we find per-household averting expenditure ranged from a low of $10.74 in our full sample specification to a high of $18.36 in a sample of non-metro and non-border county residents. Converting the sample average averting expenditure of $10.74 to an annual expenditure for the entire impacted population implies an averting expenditure in Pennsylvania shale counties exceeding $19 million for the year 2010 that increased from $12.9 million in 2009. With ongoing averting expenditures in Pennsylvania shale counties rapidly increasing along with increases in shale activity, this research establishes ongoing, persistent negative welfare impacts from perceptions of environmental risk that accrue to a broad set of households – both rural and urban.

In contrast to much of the existing asset value and capitalization literature on potential impacts, our focus on bottled water in this paper presents a widespread opportunity for households to adjust behavior in response to environmental risks without requiring individuals to absorb large transactions costs, such as moving. Overall, our results suggest there exists an immediate need for policymakers to consider issues related to both asset value capitalization and averting behavior to reassure and reduce potentially misplaced environmental risk perceptions. One option, which is currently ongoing, is mandated water testing of groundwater wells. Another possibility is to the establishment policies directed at addressing losses and potential compensation.

To provide some context to our results, in 2012 Pennsylvania adopted Act 13, which imposed an impact fee on shale production to be used to offset potential negative externalities associated with shale development and return funds to local communities. In the year 2013, over $220 million was collected for these purposes.[14] Our findings, from 2010, suggest that households spent nearly 10% of this total amount in averting expenditure, a welfare loss that is not presently accounted for in public planning legislation associated with Act 13. This suggests that substantial welfare improvements could be possible through increased education, water quality testing, and other assurances of public drinking water safety that would reduce averting expenditure in cases where water contamination is absent.

[14] To provide additional context, the gross amount of "Lease and Royalty" dollars that were taxed in these counties in 2009 and 2010 were $1.84 and $2.34 billion, respectively. The main issue to keep in mind, however, is that these amounts likely to accrue to a much smaller group of people, many of own may not even live in those counties.

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Figures

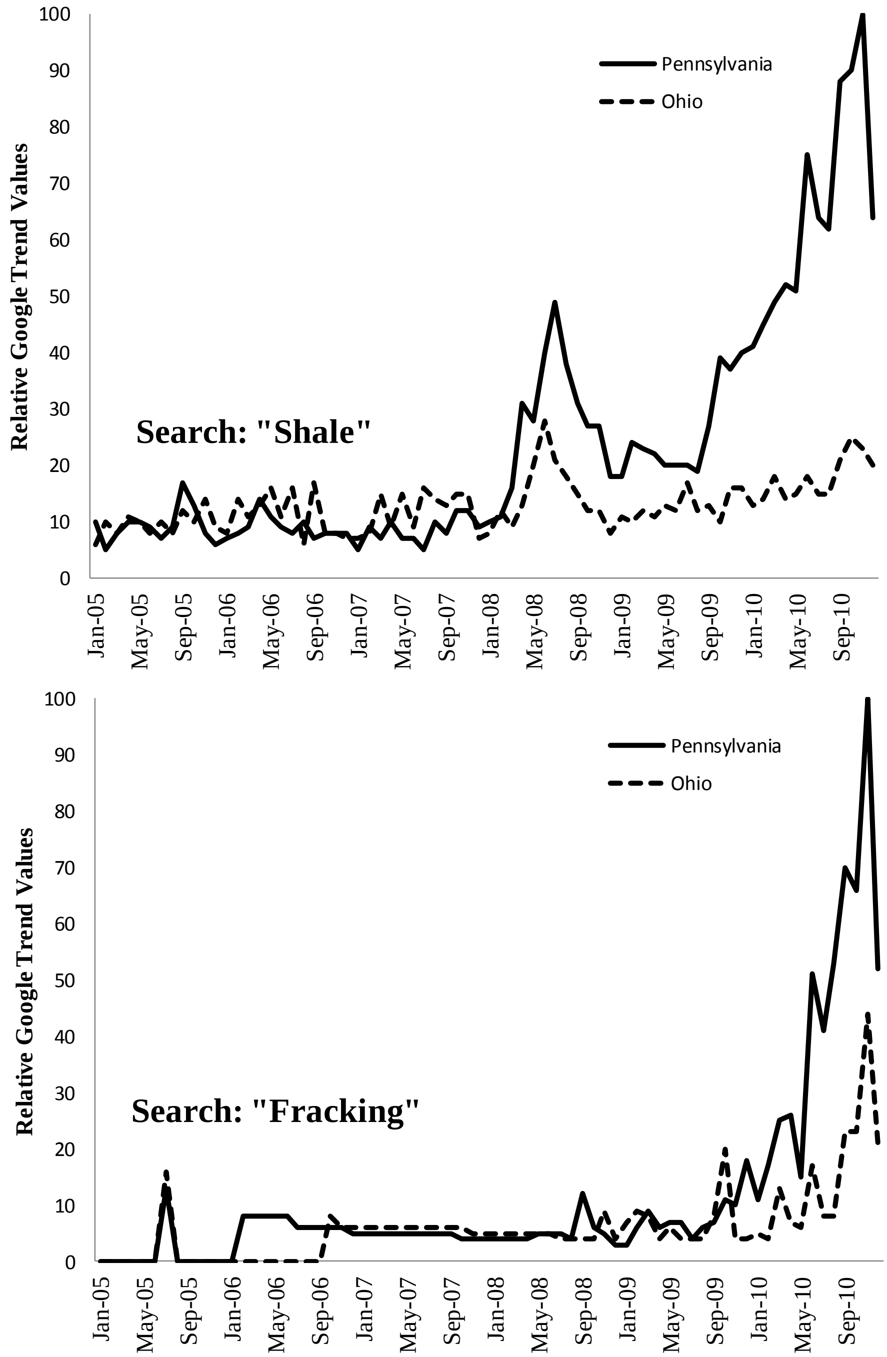

Figure 1. Google Trends Values for Pennsylvania and Ohio

Note. – This figure shows search results from Google Trends for the period 2005-2010 in Pennsylvania and Ohio based on two shale gas related search terms. The top part of the figure shows a search for “Shale”, and the bottom shows a search for “Fracking”. The results are for a joint search in both states, so the values are relative with 100 in Pennsylvania representing the maximum value for both searches and the other values being relative to this value.

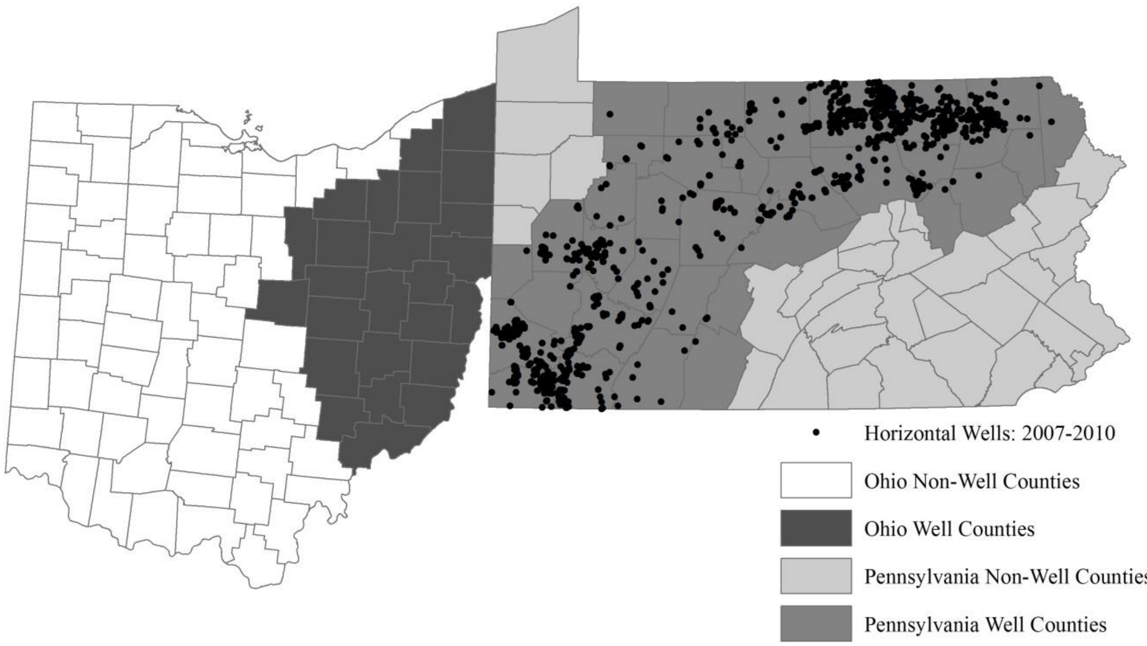

Figure 2. Treatment and Control Groups for the DD and DDD Models

Note. – This figure shows the counties in Pennsylvania and Ohio used in creating the treatment and control groups in the DD and DDD models in the paper. Non-well counties are defined as counties that never had unconventional gas development. Well counties are defined as counties that either had drilling during our study period (post-2006 for Pennsylvania) or had drilling after our study period (post-2011 for Ohio).

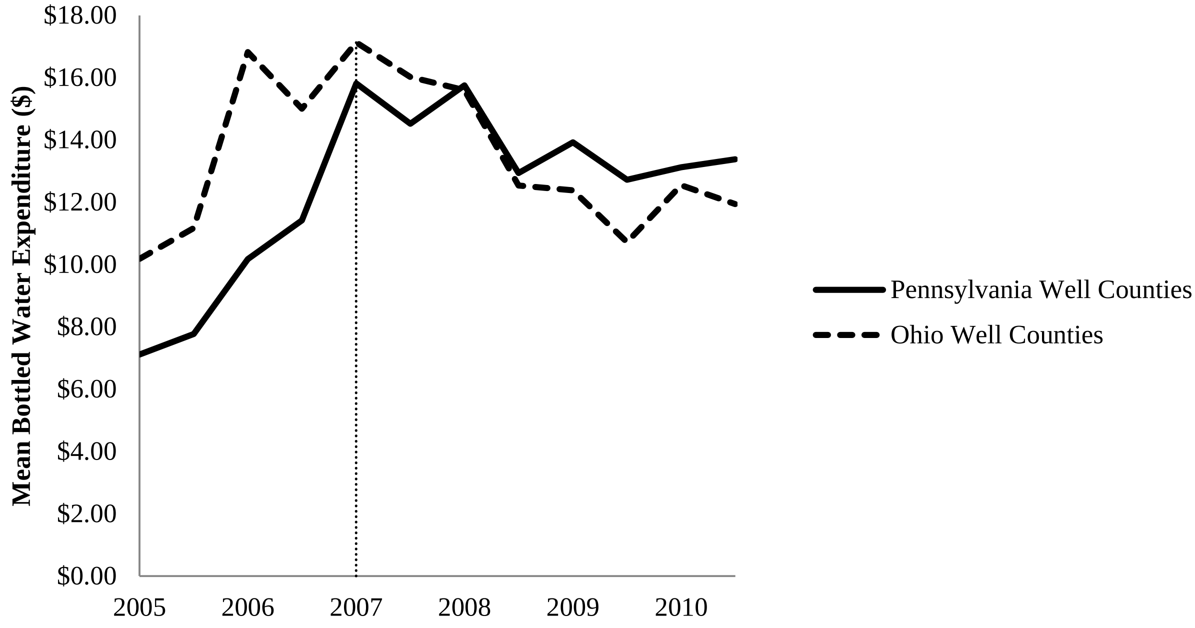

Figure 3. DD Trends for Bi-Annual Well Counties in Pennsylvania and Ohio

Note. – This figure shows trend lines for mean household bottled water expenditure for well counties in Pennsylvania and Ohio (see Figure 2 for description). The values are generated by taking the average of bi-annual household bottled water expenditure for households located in each group. The vertical line in the figure shows the cutoff date (post-2006) when unconventional gas development began in Pennsylvania.

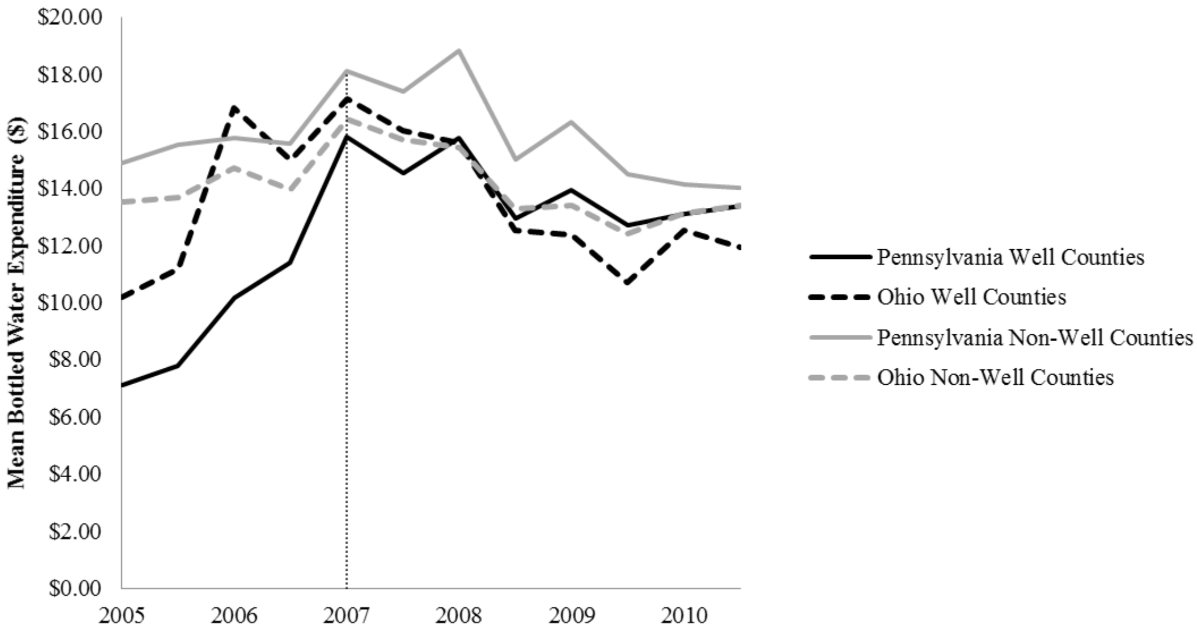

Figure 4. DDD Trends in Average Bi-Annual Expenditure for Well and Non-Well Counties

Note. – This figure shows the trend lines for average household bottled water expenditure for well and non-well counties in Pennsylvania and Ohio (see Figure 2 for description). We use these divisions in constructing the treatment variables in our DDD models. The values are generated by taking the average of bi-annual bottled water expenditure for households located in each group. The vertical line in the figure shows the cutoff date (post-2006) when unconventional gas development began in Pennsylvania.

Table 1
Summary Statistics and Comparison of Demographic Controls

	Well Counties				Non-Well Counties							
	Pre-Treatment		Post-Treatment		Pre-Treatment		Post-Treatment					
	OH	PA	OH	PA	OH	PA	OH	PA	DD		DDD	
Income ($)	42528	41883	47018	51199	51321	53257	58145	61054	4825.329	*	3845.500	
Household Size (1-6)	2.31	2.27	2.43	2.39	2.23	2.32	2.30	2.44	0.009		-0.041	
Age (Female Head of Household)	55.86	56.18	54.93	53.00	55.43	54.01	54.56	53.15	-2.250	**	-2.243	*
Education (Female Head of Household):												
HS or Less	0.04	0.04	0.04	0.03	0.03	0.04	0.03	0.03	-0.108		0.005	
HS Grad	0.39	0.42	0.39	0.37	0.34	0.38	0.31	0.36	-0.123		-0.178	
Some College	0.31	0.23	0.28	0.24	0.28	0.25	0.29	0.25	0.102		0.141	
College Grad	0.20	0.20	0.23	0.27	0.25	0.25	0.27	0.26	0.118		0.116	
Post-Grad or Professional	0.06	0.11	0.06	0.09	0.09	0.08	0.10	0.09	-0.103		-0.122	
Has Children (Under 18)	0.23	0.20	0.21	0.22	0.19	0.23	0.21	0.26	0.097		0.075	
Married	0.64	0.57	0.65	0.63	0.59	0.57	0.62	0.64	0.109		0.010	
Race (1-5):												
While	0.96	0.92	0.95	0.93	0.88	0.86	0.88	0.86	0.211		0.178	
Black	0.01	0.06	0.02	0.05	0.08	0.09	0.09	0.09	-0.574	*	-0.482	
Asian	0.00	0.01	0.00	0.00	0.01	0.01	0.01	0.01	-0.056		-0.106	
Other	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	-0.172		-0.434	*
Hispanic	0.01	0.00	0.01	0.01	0.01	0.03	0.02	0.03	0.358		0.390	
Number of Observations	506	656	2200	4153	2877	1823	9451	5878				

Note. – This table displays the means for all the demographic control variables used in the DD and DDD models. These variables come from the Nielsen HomeScan data. The summary statistics are for the full dataset (2005-2010). The final two columns - DD and DDD - compare the means in the treatment and control counties before and after the start of shale gas drilling in Pennsylvania. Statistical significance is generated by regressing each characteristic on the treatment effects variables from the DD and DDD models. The first three regressions use OLS and the remaining binary variables use a probit model. The standard errors in each model are adjusted for heteroscedasticity and clustered at the county-by-year level.

* Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level

Table 2

Comparison of Census and Nielsen Demographic Data for OH and PA

	Census	HomeScan
Median Income ($)		
OH	$48,246	$47,500
PA	$52,267	$47,500
High School Degree (%)		
OH	88.2%	96.9%
PA	88.3%	97.0%
College Degree (%)		
OH	24.7%	35.5%
PA	27.0%	35.4%
Household Size		
OH	2.47	2.35
PA	2.48	2.45
Population (%)		
OH	47.50%	54.02%
PA	52.50%	45.98%

Note. – Comparison of Nielsen data for the years 2005-2010 with census data from the years 2008-2012.

Table 3
Yearly Bottled Water Expenditure for Households in Well and Non-Well Counties

	Well Counties		Non-Well Counties	
	OH	PA	OH	PA
	Number of Counties			
	24	34	64	33
	Mean Expenditure ($)			
2005	24.30	14.88	28.39	30.84
2006	31.64	20.96	29.26	31.27
2007	32.33	30.57	32.64	36.36
2008	28.61	28.21	28.66	34.14
2009	21.95	26.51	26.05	30.27
2010	21.48	26.07	27.84	27.63
	Households in Each Group (#)			
2005	239	321	1397	884
2006	267	335	1480	939
2007	539	1018	2456	1422
2008	583	1110	2497	1551
2009	584	1091	2421	1564
2010	494	934	2077	1341

Note. – This table summarizes the data on yearly household bottled water expenditure. The first part gives the count of well and non-well counties in Pennsylvania and Ohio; the second part displays mean household expenditure ($) by year for each group; and the last section shows the number of households in each group in each year.

Table 4
DD Models

	(1)			(2)			(3)		
Variables	Coef.		St. Err.	Coef.		St. Err.	Coef.		St. Err.
Treatment Effects									
PAPost2006	10.1020	***	2.9303	8.0894	**	3.4755	7.8487	**	3.4602
PA	-8.9409	***	3.1654	-7.6539	**	3.0601	-7.4971	**	3.0425
Year2006	7.5562	***	2.4858	7.6925	***	2.8222	7.8895	***	2.8801
Year2007	8.0681	***	2.5429	6.7265	**	3.4240	7.1634	**	3.5009
Year2008	4.9431	**	2.4432	3.3298		3.1795	4.1063		3.1228
Year2009	2.1581		2.1543	0.9347		3.0897	1.7568		3.1003
Year2010	1.5051		2.4176	0.8091		3.1557	1.6635		3.2796
Other Controls									
Income				1.8E-04	***	2.5E-05	5.9E-05		6.6E-05
Household Size									
HHSize2				12.9444	***	2.2632	4.0394		4.2742
HHSize3				16.2456	***	2.6264	4.4460		5.7832
HHSize4				19.5697	***	3.4231	3.4929		6.4126
HHSize5				12.5483	***	3.9872	1.9627		7.3682
HHSize6				11.7712	**	4.9025	9.3290		10.1974
Age - Female Head				-0.1825	***	0.0582	-0.4600		0.3743
Education - Female Head									
HS Grad				0.7588		3.2036	-5.0755		6.3154
Some College				6.8683	**	3.4666	0.8512		7.2950
College Grad				2.3030		3.5705	2.1714		8.6889
Post Grad or Profession				-4.1426		3.3170	2.9384		9.7655
Has Children (Under 18)				2.4777		2.2802	5.3062		5.7306
Married				-3.0623	*	1.9196	-5.6922		5.2233
Race									
Black				-0.7989		2.0731	-4.5963		11.0456
Asian				-27.2361	***	2.3002	-4.6016		13.4808
Other				7.9118		8.0196	1.8736		6.4550
Hispanic				-10.2129		3.3447	-2.3718		11.2431
Constant	22.9981	***	2.5828	13.4777	**	5.6334	8.7774		6.4945
Mundlak Variables		No			No			Yes	
N		7515			7515			7515	
R^2		0.004			0.036			0.041	
Averting Expenditure		**\$10.10**			**\$8.09**			**\$7.85**	

Note. – The dependent variable in each model is yearly household expenditure on bottled water. The coefficients are estimated using the model in Eq. (1). The averting expenditure value from each model is generated from the coefficient on the DD variable. Model (1) is a standard DD model without household demographics or household means (Mundlak variables); models (2) and (3) both include household demographics and model (3) includes Mundlak effects. The standard errors are clustered at the county-by-year level.

* Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level.

Table 5
DDD Models

	(1)			(2)			(3)		
Variables	Coef.		St. Err.	Coef.		St. Err.	Coef.		St. Err.
Treatment Effects									
PAHasWellPost2006	9.0222	**	3.9624	8.1914	**	4.0387	7.8485	*	4.0160
PA	2.4664		1.8320	1.2795		1.8022	1.1399		1.7892
HasWell	-1.6153		2.9902	-0.4994		3.0981	-0.3511		3.0806
PAHasWell	-11.4928	***	3.5264	-10.1343	***	3.6015	-9.8623	***	3.5797
WellPost2006	0.2761		3.2907	0.0303		3.4088	-0.0633		3.3951
PAPost2006	1.1648		2.0766	0.9060		1.9972	1.0115		1.9816
Year2006	2.5222	*	1.4846	2.2597		1.4893	2.7735	*	1.4839
Year2007	5.2950	***	1.6239	3.6199	**	1.6241	4.2670	***	1.6156
Year2008	1.9607		1.5350	0.0983		1.5897	0.9241		1.5819
Year2009	-1.0160		1.6262	-2.6560		1.6564	-1.7324		1.7064
Year2010	-1.2565		1.7081	-2.1785		1.7525	-1.2039		1.8587
Other Controls									
Income				1.4E-04	***	1.2E-05	2.5E-05		3.5E-05
Household Size									
HHSize2				11.6525	***	1.2042	5.4866	**	2.4838
HHSize3				20.5916	***	1.9316	8.1905	**	3.3654
HHSize4				20.4214	***	2.0295	8.9890	**	3.9353
HHSize5				22.3276	***	2.7728	5.5536		5.3903
HHSize6				20.7259	***	2.9175	3.6312		6.9531
Age - Female Head				-0.2738	***	0.0329	-0.3942	**	0.1835
Education - Female Head									
HS Grad				-6.6271	**	2.9479	-2.8159		5.3114
Some College				-6.4387	**	3.0494	-2.3061		5.9617
College Grad				-8.8894	***	3.0607	-3.7928		6.6916
Post Grad or Profession				-13.4258	***	2.9407	-4.4547		8.9641
Has Children (Under 18)				2.7136	*	1.5985	3.5054		2.8105
Married				-3.5374	***	1.0616	-0.4491		3.8640
Race									
Black				6.8786	***	1.2198	-3.8509		6.1688
Asian				-15.8543	***	2.1282	-5.2315		10.5773
Other				3.4818		3.5570	-3.4808		7.9122
Hispanic				-3.8953	*	2.0959	-1.8548		6.4535
Constant	27.2697	***	1.3275	34.3653	***	4.5595	32.5819	***	4.8533
Mundlak Variables		No			No			Yes	
N		27544			27544			27544	
R^2		0.003			0.034			0.036	
Averting Expenditure		**$9.02**			**$8.19**			**$7.85**	

Note. – The dependent variable in each model is yearly household bottled water expenditure. The coefficients are estimated by Eq. (2). The averting expenditure value from each model is generated using the coefficient value on the treatment effect variable. Model (1) is a standard DDD model without household demographics or household means (Mundlak variables); models (2) and (3) both include household demographics and model (3) includes Mundlak effects. The standard errors are clustered at the county-by-year level.

* Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level

Table 6
DDD Models: Drop Metro Counties

Variables	(1) Coef.		St. Err.	(2) Coef.		St. Err.	(3) Coef.		St. Err.
Treatment Effects									
PAHasWellPost2006	10.8820	**	4.3823	10.2304	**	4.3992	9.5776	**	4.3917
PA	3.1825		2.2346	2.0744		2.1052	1.6860		2.1208
HasWell	-1.6477		3.0906	-0.3776		3.1536	-0.3915		3.1440
PAHasWell	-12.9480	***	3.8494	-11.6945	***	3.8697	-11.1409	***	3.8670
WellPost2006	-0.6430		3.3970	-0.8486		3.4697	-0.7405		3.4651
PAPost2006	-0.0490		2.4984	-0.4493		2.3227	-0.0806		2.3287
Year2006	3.1650	*	1.8343	2.8759	*	1.7572	3.4794	*	1.7921
Year2007	6.7035	***	1.9148	4.8588	**	1.7941	5.5436	***	1.8519
Year2008	3.0987	*	1.8732	1.0273		1.7746	1.9550		1.8483
Year2009	0.3913		1.9027	-1.4773		1.8189	-0.3307		1.9686
Year2010	-0.1962		2.0046	-1.3117		1.9507	-0.0653		2.1876
Other Controls									
Income				1.5E-04	***	1.4E-05	5.1E-05		4.1E-05
Household Size									
HHSize2				13.3575	***	1.3981	7.2276	**	3.1259
HHSize3				23.4798	***	2.2573	9.8492	**	4.1335
HHSize4				20.2906	***	2.3457	9.7772	**	4.9822
HHSize5				24.9909	***	3.0501	8.1507		6.6318
HHSize6				24.5104	***	3.4642	4.6086		8.2141
Age - Female Head				-0.2979	***	0.0385	-0.4536	**	0.2276
Education - Female Head									
HS Grad				-4.3418		3.2359	-0.9782		6.6477
Some College				-3.0181		3.3013	0.8716		7.2481
College Grad				-7.2836	**	3.4533	-2.0524		8.1756
Post Grad or Profession				-11.6829	***	3.4169	-8.1321		9.4027
Has Children (Under 18)				5.1783	***	1.9034	3.8490		3.4320
Married				-5.1560	***	1.3012	0.9037		4.4979
Race									
Black				4.1591	***	2.1699	-6.4592		7.4610
Asian				-17.3365	***	2.8392	-8.2172		10.5000
Other				3.2002		3.7034	-9.1008		6.9490
Hispanic				-0.3643	*	2.8260	-0.9961		8.2101
Constant	26.9629	***	1.5953	32.5085	***	4.5812	30.6211	***	5.2063
Mundlak Variables		No			No			Yes	
N		20083			20083			20083	
R^2		0.004			0.033			0.036	
Averting Expenditure		**\$10.88**			**\$10.23**			**\$9.58**	

Note. – The dependent variable in each model is yearly household bottled water expenditure. The coefficients are estimated by Eq. (2). The averting expenditure value from each model is generated using the coefficient value on the treatment effect variable. Model (1) is a standard DDD model without household demographics or household means (Mundlak variables); models (2) and (3) both include household demographics and model (3) includes Mundlak effects. The standard errors are clustered at the county-by-year level.

* Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level

Table 7
Treatment Variation (DDD) Based on Number of Wells Drilled

	Full DD Data			Drop Metro Counties		
Variables	Coef.		St. Err.	Coef.		St. Err.
Treatment Effects						
PAPost2006 - 1 (1-35 Wells)	7.4575	***	2.7172	9.1561	**	1.4233
PAPost2006 - 2 (36-135 Wells)	9.5467	**	3.8538	10.7257	***	2.0728
PAPost2006 - 3 (136 or More Wells)	9.9978	*	5.9748	11.3043	*	4.8479
PA	1.1931		1.7658	1.7728		
PA - 1 (1-35 Wells)	-9.3855	***	1.8751	-10.7693	***	0.9114
PA - 2 (36-135 Wells)	-11.2964	***	3.0360	-11.8233	***	1.0099
PA - 3 (136 or More Wells)	-13.2969	***	4.9535	-13.9238	***	4.7732
HasWellPost2006	-0.4174		1.4494	-1.1339		
PAPost2006	0.9581		1.9629	-0.1672		
Year2006	2.7831	*	1.4868	3.4893	*	0.9564
Year2007	4.3241	***	1.5411	5.6342	***	1.9867
Year2008	0.9817		1.4965	2.0462		1.5347
Year2009	-1.6737		1.6197	-0.2380		2.0106
Year2010	-1.1446		1.7715	0.0279		2.1907
Constant	32.5070	***	4.7678	30.5058	***	5.0838
N	27544			20083		
R^2	0.036			0.036		
Averting Expenditure - 1 (1-35 Wells)	**$7.46**			**$9.16**		
Averting Expenditure - 2 (36-135 Wells)	**$9.55**			**$10.73**		
Averting Expenditure - 3 (136 or More Wells)	**$10.00**			**$11.30**		

Note. – The dependent variable in each model is yearly household bottled water expenditure. The coefficients estimates are based on Eq. (2). The averting expenditure values are based on the coefficients on the treatment variables for the different levels of well activity. The first model includes all demographic controls and Mundlak effects; the second model includes the same set of covariates, but drops all households located in metro counties. The standard errors are clustered at the county-by-year level.

* Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level

Table 8
DDD: Yearly Treatment Effects

	Full DDD Data			Drop Metro Counties		
Variables	Coef.		St. Err.	Coef.		St. Err.
Treatment Effects						
PAHasWell2006	-4.5905		6.1254	-0.7951		6.3298
PAHasWell2007	1.8181		5.7029	5.6490		5.7148
PAHasWell2008	2.2108		4.8096	5.0927		5.5012
PAHasWell2009	7.3020	*	4.3050	10.7140	**	5.0118
PAHasWell2010	10.7386	**	5.0476	15.6438	***	5.7521
PAInd	0.8897		3.0548	2.5915		3.5272
HasWell	-4.8953		3.4730	-4.1016		3.6191
HasWellPA	-7.3970		4.4774	-10.6600	**	4.8412
HasWell2006	8.6545		5.5345	7.0526		5.5076
HasWell2007	6.4625		5.2239	4.8379		5.0529
HasWell2008	6.1672	*	3.8648	5.4835	*	4.0378
HasWell2009	3.5462		3.3632	1.8260		3.5442
HasWell2010	1.4482		3.9449	-0.7078		4.1123
PA2006	0.4868		2.1988	-1.7546		2.3792
PA2007	1.2105		2.9032	-1.0904		2.9118
PA2008	2.8256	**	2.7377	1.5195	**	3.4889
PA2009	2.0763	*	3.2411	-0.0087		3.7972
PA2010	-1.4571		3.7809	-4.9904		4.1653
Year2006	1.3650		1.4649	2.7368	*	1.3880
Year2007	3.6644	*	2.0425	5.2263	***	1.5997
Year2008	-0.4093		1.5262	0.2751		1.8397
Year2009	-2.9331		2.2546	-1.1216		2.4389
Year2010	-0.7911		2.8823	1.5095		3.0439
Constant	33.2836	***	7.5698	30.9681	***	8.2187
N	27544			20083		
R^2	0.036			0.036		
Averting Expenditure: 2010	**$10.74**			**$15.64**		

Note. – This table shows results for a series of yearly DDD models estimated based on Eq. (3). The averting expenditure values are generated using the coefficient values on the treatment effects variables for the year 2010. The first model is a full version of Eq. (3) with demographic controls and Mundlak effects; the second model includes the same set of covariates, but drops all households located in metro counties. The standard errors are clustered at the county-by-year level.

* Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level

Table 9
Yearly DDD: Spillover Effects

Variables	Drop Border Counties Coef.		Drop Border Counties St. Err.	Drop Border and Metro Counties Coef.		Drop Border and Metro Counties St. Err.
Treatment Effects						
PAHaswell2006	-4.8793		6.2744	6.5553		-0.0800
PAHaswell2007	1.5772		5.9585	5.1584		6.0979
PAHaswell2008	2.8733		5.0095	5.4482		5.9471
PAHaswell2009	10.1097	**	4.6425	13.3470	**	5.5856
PAHaswell2010	13.5111	**	5.5022	18.3637	***	6.4581
PA	0.9428		3.4021	2.9245		4.2344
HasWell	-5.7785		3.5769	-5.4244		3.8703
PAHasWell	-7.5270		4.7824	-11.1117	**	5.4204
HasWell2006	9.3645	*	5.5362	7.6482		5.5149
HasWell2007	6.8321		5.3405	5.8758		5.1537
HasWell2008	6.0781		3.9248	6.1979		4.2410
HasWell2009	2.9138		3.5473	2.2423		3.9575
HasWell2010	0.6791		4.2538	-0.2539		4.6922
PA2006	0.8125		2.4767	-2.0333	**	2.8186
PA2007	1.5413		3.3480	-0.4896		3.6393
PA2008	2.0823		3.1627	1.0233	*	4.3091
PA2009	-0.6936		3.6251	-2.6113	**	4.5861
PA2010	-4.1706		4.3147	-7.6593	*	5.0715
Year2006	0.5929		1.4235	2.0831		1.3794
Year2007	3.2355		2.2914	4.0713	*	1.8645
Year2008	-0.3222		1.6772	-0.5463		2.2766
Year2009	-2.2318		2.5237	-1.5604		3.0493
Year2010	0.1038		3.3352	1.0775		3.8445
Constant	32.4579	***	8.3876	31.5075	***	9.3036
N		23302			16975	
R^2		0.036			0.037	
Averting Expenditure: 2010		**\$13.51**			**\$18.36**	

Note. – This table shows results for two yearly DDD models estimated: (1) after dropping all border counties - all non-well counties that border well counties in both Pennsylvania and Ohio; and (2) after dropping both border counties and all households in metro counties. The models are estimated based on Eq. (3). The averting expenditure values are generated using the coefficient values on the treatment effects variables for the year 2010. All models includes demographic controls and Mundlak effects. The standard errors are clustered at the county-by-year level.

* Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level

Table 10
Yearly DDD: Water Volume

	Full DDD Data			Drop Metro Counties		
Variables	Coef.		St. Err.	Coef.		St. Err.
Treatment Effects						
PAHasWell2006	-66.885		359.214	-14.840		393.147
PAHasWell2007	288.515		345.392	477.662		365.387
PAHasWell2008	170.485		353.251	305.612		410.309
PAHasWell2009	601.498	*	335.612	891.288	**	433.079
PAHasWell2010	728.671	*	391.479	1113.118	**	443.440
PA	273.811		238.668	318.145		316.832
HasWell	-428.019	*	220.885	-435.337	*	261.479
HasWellPA	-801.474	**	308.909	-914.886	**	382.689
HasWell2006	654.285	**	313.911	617.168	*	329.085
HasWell2007	575.635	*	296.287	505.148	*	303.509
HasWell2008	632.674	**	272.767	631.597	**	307.176
HasWell2009	451.976	**	226.192	369.249		273.375
HasWell2010	173.253		300.904	40.004		328.035
PA2006	-117.360		144.372	-141.567		184.968
PA2007	-66.782		206.093	-118.518		234.257
PA2008	35.410		226.825	43.071		302.227
PA2009	45.377		224.185	-20.731	**	294.327
PA2010	-104.667		266.221	-333.999		306.203
Year2006	135.625	*	76.456	155.082		113.179
Year2007	334.361	**	147.544	398.997	**	153.390
Year2008	140.590		133.474	144.450		184.725
Year2009	-78.054		165.139	14.335		216.192
Year2010	156.392		203.888	302.772		227.992
Price of Water	-4.80E+04	***	5188.734	-5.21E+04	***	4856.643
Constant	3330.206	***	495.946	3480.476	***	595.896
N		27544			20083	
R^2		0.062			0.063	
Averting Expenditure: 2010		**$11.46**			**$17.50**	

Note. – The dependent variable in each model is yearly household bottled water consumption, in ounces. The coefficients are estimated by Eq. (3) and each model includes, in addition to the demographic controls, the median price per ounce of water paid by each household in each year. The averting expenditure value from each model is generated by multiplying the coefficient value on the treatment effect variable for the year 2010 by the mean price per ounce of water across all households in the treated counties in the year 2010. The first model is a full version of Eq. (3) with demographics controls and Mundlak effects; the second model includes the same set of covariates, but drops all households in metro counties. The standard errors are clustered at the county-by-year level.

* Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level

Table 11
Testing for Income Effects Using Yearly Household Expenditure on Other Categories of Goods

Variables	Total Expeniture minus Beverages Coef.		Total Expeniture minus Beverages St. Err.	Fresh Produce Coef.		Fresh Produce St. Err.	Fresh and Frozen Meat Coef.		Fresh and Frozen Meat St. Err.	Bread, Cereals, Grains, and Pasta Coef.		Bread, Cereals, Grains, and Pasta St. Err.	Cheese and Yogurt Coef.		Cheese and Yogurt St. Err.
Treatment Effects															
PAHasWell2006	-13.1395		100.6484	-11.9406		8.7999	-6.5118		6.5086	5.6532		14.4225	-6.5118		6.5086
PAHasWell2007	-5.9611		78.6318	-20.2998	***	7.7298	-19.7674	***	4.7285	16.9621		12.0099	-19.7674		4.7285
PAHasWell2008	-50.2822		79.1295	-19.0321	**	7.7154	-19.7832	***	4.7240	6.9366		12.2032	-19.7832		4.7240
PAHasWell2009	-74.9301		99.7588	-14.2287	*	8.4464	-9.4660		6.3483	-3.9433		13.7983	-9.4660		6.3483
PAHasWell2010	-60.0372		90.4844	-11.5953		8.5256	-11.2368	*	6.0564	4.5286		12.7398	-11.2368		6.0564
Constant	1231.3610	***	54.0398	48.7236	***	4.7585	59.3529	***	3.8735	61.9961	***	7.9193	67.7536	***	4.8471

Note. – This table presents results from a series of yearly DDD models (Eq. 3) estimated after replacing the dependent variable of yearly household bottled water expenditure with yearly household expenditure on all of the products from each of the categories listed in the table. The purpose of estimating these models is to try and gauge whether there are income effects associated with the increased gas drilling in our treatment counties - i.e., is all of the increased expenditure on bottled water a result of rising incomes and not of increases in risk perceptions. Each category represents a different set of products that households may increase their expenditure on if their incomes rose as a result of increased drilling activity. Each model includes a full set of demographics controls and Mundlak variables. The standard errors are clustered at the county-by-year level. N = 27,544.

* Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level

Table 12
Testing for Income Effects Using Yearly Non-Metro Household Expenditure on Other Categories of Goods

	Total Expeniture minus Beverages			Fresh Produce			Fresh and Frozen Meat			Bread, Cereals, Grains, and Pasta			Cheese and Yogurt		
Variables	Coef.		St. Err.	Coef.		St. Err.	Coef.		St. Err.	Coef.		St. Err.	Coef.		St. Err.
Treatment Effects															
PAHasWell2006	-43.1322		114.6772	-8.4674		9.0498	-10.7696		7.8169	6.2676		16.2270	-0.8559		11.6409
PAHasWell2007	16.5026		94.3600	-13.0495	*	7.6301	-20.5396	***	5.9344	9.7233		13.6565	6.8061		10.2921
PAHasWell2008	-4.8880		95.3596	-12.1441		7.6214	-20.6509	***	5.9218	3.8257		13.9434	1.8379		10.9421
PAHasWell2009	-9.7775		109.8984	-11.1276		8.5629	-12.5277	*	7.4059	-3.8958		14.1920	-1.8989		10.8623
PAHasWell2010	-11.7352		104.6776	-8.6681		8.6364	-14.1386	*	7.2638	3.1804		14.2900	2.3345		10.5409
Constant	1182.9770	***	66.9023	49.5733	***	5.2952	65.1945	***	4.9907	50.7997	***	9.9400	64.6053	***	6.0235

Note. – This table presents results based on the same series of models as Table 11, but estimated after dropping households located in metro counties. N = 20,084.
* Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level

Table 13

Safe Drinking Water Act Violations in Pittsburgh Region

Variables	Coef.		St. Err.
Treatment Effects			
SDWA TTHM Violations	2.2429	***	0.5830
Year2006	-3.5745		(3.038)
Year2007	2.0425		(3.071)
Year2008	-9.5233	**	(4.280)
Year2009	- 12.3692	**	(4.529)
Year2010	-3.2812		(3.036)
Constant	-8.8881		(7.687)
N		1,684	
R^2		0.059	
Averting Expenditure (SDWA Violation)		**$2.24**	

Note. – The model includes demographic controls, County FEs, Year FEs, and Mundlak effects. The model is estimated using a sample that drops all households located outside Allegheny County, PA and Washington County, PA. The standard errors are clustered by county and year.

* Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level

Table 14
Total Averting Expenditure

Model Specification	Coefficient	Households	Total Expenditure
DD Models			
Full Dataset	$7.85	1,770,084	$13,895,159
DDD Models			
Full Dataset	$7.85	1,770,084	$13,895,159
Drop Metro Counties	$9.58	1,276,799	$12,231,734
DDD: Heterogeneous Treatment Effects			
1-35 Wells	$7.46	1,124,548	$8,389,128
36-135 Wells	$9.55	439,659	$4,198,743
136 or More Wells	$10.00	205,877	$2,058,770
Total			$14,646,642
DD: Heterogeneous Treatment Effects - Drop Metro Counties			
1-35 Wells	$9.16	631,262	$5,782,360
36-135 Wells	$10.73	439,659	$4,717,541
136 or More Wells	$11.30	205,877	$2,326,410
Total			$12,826,311
DDD: Yearly Treatment Effects			
2009	$7.30	1,770,084	$12,921,613
2010	$10.74	1,770,084	$19,010,702
Average			$15,966,158
DDD: Yearly Treatment Effects - Drop Metro Counties			
2009	$10.71	1,276,799	$13,674,517
2010	$15.64	1,276,799	$19,969,136
Average			$16,821,827
DDD: Spillover Effects			
2009	$10.11	1,770,084	$17,895,549
2010	$13.51	1,770,084	$23,913,835
Average			$20,904,692
DDD: Spillover Effects - Drop Metro Counties			
2009	$13.35	1,276,799	$17,045,267
2010	$18.36	1,276,799	$23,442,030
Average			$20,243,648

Note. – This tables presents calculations for the total averting expenditure increase realized in the treatment counties in Pennsylvania relative to the rest of the counties in Pennsylvania and Ohio. The average averting expenditure values are taken directly from the coefficients in the individual models. The number of households is based on the total population in the treated counties in Pennsylvania. The total number of households is derived by dividing total population by 2.48 persons per household.

Appendix

Table A1
Robustness Check for Sorting and Sample Attrition

Variables	(1) Coef.		St. Err.	(2) Coef.		St. Err.
Treatment Effects						
PAHasWell2006	0.0609		8.2719	1.4896		10.2498
PAHasWell2007	1.8487		7.6151	4.3104		9.9160
PAHasWell2008	2.4703		6.8449	1.7052		8.8608
PAHasWell2009	11.4391	*	6.6836	11.8106		8.1444
PAHasWell2010	15.8443	**	7.2917	19.5869	**	8.5197
PAInd	4.3626		4.4302	8.3158		5.4161
HasWell	-5.1656		3.8091	-5.0851		3.8067
HasWellPA	-13.6271	**	5.8187	-17.8534	**	7.0828
HasWell2006	7.7494		6.3208	7.8003		6.3185
HasWell2007	5.9428		5.4171	5.9229		5.4190
HasWell2008	6.2153	*	4.5206	6.1415		4.5147
HasWell2009	2.2863		4.5497	2.2475		4.5537
HasWell2010	-0.2548		5.0115	-0.2903		5.0335
PA2006	-2.3195		5.2302	-4.2169		6.5959
PA2007	-2.2786		4.8841	-1.1154		6.2660
PA2008	0.9492		4.8562	1.0926		6.3207
PA2009	-3.8129		4.8773	-3.8342		6.0493
PA2010	-8.5217		5.3891	-10.9615	*	6.1385
Year2006	1.9415		2.9778	1.9628		2.9843
Year2007	3.9511		2.5771	3.9342		2.5924
Year2008	-0.6304		2.5132	-0.5971		2.5356
Year2009	-1.6123		2.8680	-1.6415		2.9027
Year2010	1.0401		3.4734	1.0770		3.5281
Constant	31.2748	***	6.6252	29.7574	***	7.1836
N		13074			11459	
R^2		0.042			0.041	
Averting Expenditure: 2010		**$15.84**			**$19.59**	

Note. – Both models are estimated using Eq. (3) and include demographic controls, Mundlak effects, and drop all households located in metro and border counties. Model (1) is estimated using a sample that drops all households located in treatment counties that are not present in the data both before and after the start of shale gas development. Model (2) is estimated by further excluding households from treatment counties that are not in the sample in every period. The standard errors are clustered at the county-by-year level.

* Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level

Table A2
Probit Model of Attrition

Variables	Coef.		St. Err.
Treatment Effects			
PAHasWellPost2006	-0.1005		0.118
PA	-0.0057		0.055
HasWell	-0.0963		0.070
PAHasWell	0.0938		0.102
WellPost2006	0.1550	*	0.081
PAPost2006	0.0434		0.063
Year2006	0.3077	***	0.046
Year2007	0.1633	***	0.053
Year2008	-0.3192	***	0.047
Year2009	-0.5587	***	0.046
Year2010	-0.8317	***	0.046
Constant	-0.3525	***	0.093

Note. – The dependent variable in the probit model is an indicator for a household's presence in the sample taking a value of 1 if present and zero if absent. The sample (N = 19680) includes a squared dataset of all households observed in the pre-treatment period (2005-2006). Standard errors are clustered at the county-by-year level. Results indicate no systematic attrition in treated counties.

* Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level

Table A3
Data on Total and Promotional Water Sales

	Well Counties		Non-Well Counties	
	Pennsylvania	Ohio	Pennsylvania	Ohio
A.	Total Water Purchases (#)			
2005	1379	1325	7086	9506
2006	1776	1873	7634	11142
2007	8303	4372	13129	20666
2008	8688	4700	13987	19743
2009	7827	4064	13390	17498
2010	6766	3454	10982	16045
B.	Total Promotional Water Purchases (#)			
2005	399	314	2083	2908
2006	519	499	2539	3518
2007	1554	924	3948	5877
2008	1463	860	4156	5528
2009	1508	806	3907	5195
2010	1456	819	3477	5118
C.	Proportion of Purchases on Promotion (%)			
2005	28.93	23.70	29.40	30.59
2006	29.22	26.64	33.26	31.57
2007	18.72	21.13	30.07	28.44
2008	16.84	18.30	29.71	28.00
2009	19.27	19.83	29.18	29.69
2010	21.52	23.71	31.66	31.90

Note. – This table summarizes the data on total water purchases. Part A. shows the count of total bottled water sales by year; part B. shows the count of total bottled water sales that were discounted or "on promotion"; and part C. shows the percentage of sales that were on promotion.