Office Visits Preventing Emergency Room Visits: Evidence from the Flint Water Switch

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Abstract

Emergency department visits are costly to providers and to patients. We use the Flint water crisis to test if an exogenous increase in office visits reduced avoidable emergency room visits. In September 2015, citizens in Flint became aware of increased lead levels in their drinking water, resulting from the switch from Lake Huron to the Flint River. Using Medicaid claims for 2013-2016, we find that this information shock increased the share of enrollees with lead tests by 3.2 percentage points and the share with any office visit by 1.1 percentage points (4.2%). This led to a reduction of 3.3 preventable, non-emergent, and primary care treatable emergency room visits per 1000 eligible children (5.4%), suggesting an elasticity of substitution of -1.3. This decrease is present in shifts from emergency room visits to office visits across several common conditions. However, total payments increased by $51 dollars per Medicaid recipient-month. So while office visits reduced inefficient ER visits, overall health care costs increased. Furthermore, this $51 corresponds to an additional $2.3 million per year, which is comparable to the entire projected savings from the water switch ($2.5 million per year). Our ER results are potentially applicable to any situation in which individuals are induced to seek more care in an office visit setting.

JEL Codes: *Medicaid; Lead; Environmental Regulation; Emergency Care*

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Introduction

Emergency departments (ED) are structured to diagnose and treat emergent conditions. As such, they may be an expensive alternative to primary care, to both the individual patient and to the health care system. For many individuals, they are the only option for healthcare, with those who lack access to primary care substituting to ED care (Grumbach, Keane, and Bindman 1993). Many of these individuals are of low socio-economic status, and so possibly eligible for Medicaid. While multiple studies have demonstrated that expanded access to Medicaid increases emergency room usage (Taubman et al. 2014; Nikpay et al. 2017),[1] no study has been able to isolate the causal link between increased primary care and emergency room usage for those who are already eligible for Medicaid.

In this paper, we exploit a shock to primary care (measured by office visits) resulting from the Flint water contamination as exogenous variation. On April 25, 2014, under state-appointed emergency management, the city of Flint switched its water source from Lake Huron to the Flint River. This new source needed to be treated with strong disinfectants, which made it substantially more corrosive than the old water, leaching lead out of the existing Flint water delivery system into residential water (Masten et al. 2016). However, during the period in which water was sourced from the Flint River, local officials stressed that the city water was safe for consumption. Despite warnings and boil advisories in August and September 2014, and an EPA violation for exceeding the organic chemical thresholds in the water in December 2014, the high level of lead content in the water was largely unconfirmed until September 2015. We use this last date as the start of the "treatment" period for our analysis, because it represents the point at which city officials first issued a lead advisory in the face of a preponderance of evidence that

[1] Some argue that ED visits increase, while others argue the increase is simply a shift in payer case mix (see e.g. (Antwi et al., 2015; Finkelstein et al., 2016; Sommers et al., 2016; Sommers & Simon, 2017).

Flint's drinking water was hazardous to its residents' health.[2]

Though given a stronger regulatory environment and quality control this study context may have been avoidable, the inevitability of this shock is immaterial for our study as individuals in Flint were greatly affected by this change in water and the resulting fallout. They suffered higher levels of exposure to lead and a great deal of stress and uncertainty. Both the exposure and mental stress likely translated to higher levels of medical care utilization.

The goals of this paper are twofold. First, we establish the extent to which the knowledge of the water problems affected health care receipt. Then, we examine whether a change in primary care use leads to a reduction in, or a change in the distribution of ED visits towards fewer visits that are either treatable or preventable through primary care visits.

Whether, and to what extent, environmental disasters and interaction with policy increases medical expenditures of the affected population remains an open empirical question. We determine the amount of medical services received by individuals in the affected areas before, during, and after a water change and a revelation of exposure to contaminated water. We find that Medicaid enrollees in Flint received lead tests at twice the rates of enrollees from control cities following the information shock. The share of enrollees with any office visit increased by 1.1 percentage points, or 4.2 percent. This increase in office visits led to a reduction of 3.3 preventable, non-emergent, and primary care treatable (which we aggregate as "avoidable") emergency room visits per 1000 eligible children (5.4%), which suggests an elasticity of substitution of -1.3.

Total payments per Medicaid recipient-month increased by $51 despite this shift away from ED care, constituting an additional $2.3 million per year in costs to the Medicaid system for

[2] We also estimate a flexible time form specification using two time periods -- January to August 2015, and September 2015 to December 2016 – with similar findings. These results are presented in Appendix C.

the Flint population, which is of the same order of magnitude as the entire projected savings from the water switch ($2.5 million per year).

The remainder of the paper proceeds as follows. First, we summarize the events surrounding the Flint water contamination, followed by a review of current literature on lead and its effect on health and other relevant literatures. Next, we discuss the data and the methods used to identify changing utilization of medical services. The following section presents results. We then discuss our findings in the context of the Flint contamination, and conclude.

Background on the Flint Water Switch

In spring 2013, as part of an effort to reduce the budget of a city under emergency management, the state-appointed manager of Flint ordered the city water supply to be switched from water sourced from the Detroit Water and Sewerage Department (DWSD) to the Flint River by April 25, 2014 (Kennedy 2016). The switch was intended to be a temporary measure until a proposed pipeline could be completed to supply Flint with water from Lake Huron independently. The Flint Water Service Center (FWSC), however, was ill-equipped to supply adequate quality water to the city since it had not supplied the city since 1967, and was not given sufficient adjustment period to build up materials, facilities, and expertise to do so (Masten et al. 2016).

The shortcomings of the new facility became quickly apparent following the switch. Initially, the water was underchlorinated resulting in water boil advisories issued in July and August of 2014 to counteract E. coli and coliform bacteria detected in the water supply.

While chlorine levels were adjusted throughout the summer months to address the bacterial presence, levels of corrosion inhibitors were not. In October 2014, General Motors Corporation complained about the corrosiveness of the water on its engine parts, and switched to an alternate source of water supply.

During this time the water supply was highly corrosive, leading to red water and discoloration throughout the water system, and an unusually large number of water main breaks (Masten et al. 2016). The heavily chlorinated water corroded at the lining of city and residential pipes, resulting in leaching of lead into the water supply.

The first high lead measurements in the city were detected in February 2015. City authorities assured residents that these measurements were outliers and that the water was safe to drink. By August 2015, Marc Edwards at Virginia Polytechnic Institute and State University had analyzed 120 samples from Flint homes, finding that 20% of samples exceeded the EPA threshold of 15 μg/L action level. In September 2015, city authorities acknowledged the widespread lead contamination of the water supply, issued a lead advisory, and switched back to Lake Huron water treated by DWSD on October 16, 2015. A more detailed history of Flint and the timeline of the water contamination is presented in Appendix A.

The timeline of the water contamination presents an interesting challenge to our analysis. While the water supply was switched in April 2014, and the first high lead measurements were disclosed in February 2015, residents did not have confirmation of the contamination until September 2015. While other studies measure the effect of exposure to lead contamination, we focus on the behavioral response to the knowledge of the contamination. Thus, our analysis focuses on medical utilization after September 2015 as the "treatment" period.

Literature Review

We contribute to several literatures in this study including those corresponding to lead exposure, the Flint water crisis, the unintended consequences of environmental or informational shocks on healthcare, and the substitutability of healthcare sources for emergency care. We discuss each in turn below.

Prior to the 1980's lead was used extensively in household paint and plumbing, particularly in the lining and soldering joints of copper pipes to help avoid leaks. As the toxicity of lead became better understood, however, such materials have been banned from new housing. Communities with older housing, such as those in Flint, are particularly vulnerable to lead contamination due to lack of investment in new plumbing.

Chronic exposure to lead has significant health consequences. High levels of lead in the bloodstream are associated with cardiovascular problems, high blood pressure, and developmental impairment affecting sexual maturity and the nervous system (ATSDR 2007; Zhu et al. 2010). Newer research, however, shows adverse outcomes at low levels of exposure, as well (Canfield et al. 2003; Jusko et al. 2008; Lanphear et al. 2005; Menke et al. 2006; Navas-Acien et al. 2007; Tellez-Rojo et al 2006). Reports from Flint suggest that children's blood lead levels increased within a few months following the water change (Hanna-Attisha et al. 2016; Zahran et al. 2017) while fertility rates dropped substantially (Grossman and Slusky 2019).

We also contribute to the literature investigating unintended consequences of environmental and informational shocks. While these unintended consequences are generally negative, this is not always the case. Deryugina and Molitor (2019) find that Medicare beneficiaries displaced by Hurricane Katrina who moved to lower mortality areas had lower mortality rates following the disaster. In our study, we see children are induced by the information shock to go see a primary care physician. The likelihood to seek preventive care and access to primary care physicians are positively correlated with household income (Sommers et al. 2017; Pitts et al. 2010). Others have attempted to study the causal effect of primary care on ED visits by incentivizing patients to visit their primary care physician (Bradley et al. 2012; 2018; Bradley and Neumark 2017). The effects of these interventions depends on the insurance status of the participants. Using an RCT design, Bradley et al. (2018) find that those receiving the cash incentive are more likely to see a primary care physician and less likely to have a preventable ED visit. However, they find no change in overall costs due to an increase in outpatient visits. We build on this research by investigating a plausibly exogenous information shock to explore a similar research question in a quasi-experimental setting.

Data

Through an agreement with the Michigan Department of Health and Human Services (MDHHS), we link vital records for all children born in Michigan in 2013-2015 with their Medicaid claims files (both fee-for-service and managed care) for any enrollees in the sample. This unique dataset has several advantages. First, the dataset includes geocoded maternal residential address at the time of birth. Second, it contains birth certificate information about parental-demographic characteristics (e.g., race and educational attainment), and important measures of health at birth (e.g., birthweight, APGAR score, gestational age). Third, the Medicaid data is at the claim level, with detailed information regarding every procedure, test, and visit. Fourth, the Medicaid data also includes payment information for all fee-for-service visits, allowing us to extrapolate payments to the managed-care claims, for complete cost information.[3] These data include Medicaid claims for the years 2013-2016.[4]

We classify Medicaid claims data using the New York University Emergency Department (NYU ED) visit severity algorithm.[5] For this, researchers reviewed ED records from the 1990s and categorized diagnosis codes (that did not include any alcohol, drug, injury, or mental health elements) into the following mutually exclusive, collectively exhaustive categories (Billings, Parikh, Mijanovich 2000; validated by Ballard et al. 2010):

- Emergent, ED care needed, and non-preventable (e.g., appendicitis)
- Emergent, ED care needed, but would have been preventable given adequate previous non-emergency care (e.g., diabetes, asthma)
- Emergent, care needed within 12 hours, but primary care would suffice (e.g., heartburn, eye pain)
- Non-emergent, care within 12 hours unnecessary (e.g., rubella, sunburn, jaw pain)

Many diagnoses do not always fall into the same category. For example, based on other details on the discharge record, out of 100 cases of:

- Croup: 57% are emergent and non-preventable, 19% are primary care treatable, and 24% are non-emergent.
- Cough: 12% emergent and non-preventable, 24% are primary care treatable, and 65% non-emergent
- Acute tonsillitis: 6% emergent but preventable, 28% primary care treatable, and 66% non-emergent.

Finally, some diagnoses could not be assigned to a category and so are listed as "unclassified".[6]

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[3] We apply cost information for managed care claims by matching procedure codes with payment made for fee-for-service procedures. Therefore, our cost estimates represent the upper range of costs to Medicaid, though are closer in line with costs for those who are privately insured.

[4] We have received approval to supplement our analysis with Medicaid claims data covering 2017 and 2018 once the data become available.

[5] https://wagner.nyu.edu/faculty/billings/nyued-background

[6] Results which incorporate a "patch" that captures and classifies a share of uncategorized diagnosis codes (Johnston et al. 2017) are presented in Appendix B.

Methodology

This research allows us to track the use of medical services by children born in Flint between 2013 and 2015, from birth to age 3 and compare them to similarly aged children born elsewhere in the state of Michigan. A priori, we expect to identify higher incidence of adverse health outcomes, increased use of primary care, and increased costs for patients and insurers due to both necessary and unnecessary additional care in Flint. We define and discuss these terms in more detail below.

Since the data are observational, we adjust for the differences between residents of Flint and those in the rest of the state. We follow the estimation method used by Grossman and Slusky (2019) which compares Flint to a subset of other large cities in Michigan. We focus exclusively on Michigan because we have complete Medicaid data for this state. Because we are interested in the behavioral response to information shocks as well as changes in water quality, we focus on September 2015, when Flint first released a public lead advisory.[7]

We employ a difference-in-differences empirical strategy presented below:

$$Outcome_{ict} = a + \beta_1 Flint * After_{ct} + \beta_2 X_{ict} + \alpha_c + \delta_t + \varepsilon_{ict} \quad (1)$$

in which *Outcome* is the medical service or procedure for individual *i* in city *c* at time *t* aggregated over the calendar month. *Flint*After* is a binary variable equal to 1 for Flint after the contamination or information shock and 0 otherwise. We include binary variables for the city in which an individual lived at the time of birth, α_c, which controls for time-invariant characteristics of a city, and year and month of service as well as year and month of birth fixed effects, δ_t, which control for general trends and seasonality in receipt of a given medical service.

[7] Mona Hanna-Attisha, a Flint pediatrician, held a press conference to announce her findings of a substantial increase in children with high blood-lead levels in September 2015, while Marc Edwards of Virginia Tech released his team's findings of high lead levels in Flint households in August 2015. Flint switched off Flint River water on October 16, 2015.

These fixed effects subsume the main effects for *Flint* and *After*. X_{ict} are individual-level characteristics or characteristics of a given city that vary over time. A potential confounder in our study is that the state of Michigan expanded Medicaid coverage through the ACA in 2014. To the extent that this expansion affected all parts of Michigan equally, this will be captured by the time fixed effects.[8] We investigate the percentage of the sample reporting: any lead test; any office visit; any ED visit; and any claims. We also investigate the total number of claims, and the total payments made. Standard errors are clustered at the city level to allow for serial correlation.

We use a slightly modified version of the above equation to investigate the impact of the water switch on different types of ED visits, defined by the NYU algorithm. For each category, at the individual-month level, we construct a per capita outcome variable by summing the fractional shares of each claim in that category. For example, if an individual had two discharges in a given month, one that was 20% preventable with primary care and the other 70% preventable with primary care, we assign a value of 0.9. Anyone without an ED claim in that category (or with no ED claims at all) receives a value of 0.

While coding those with no claims as having zero visits in a linear specification may bias the results (as some of the individuals would ideally have a negative number of emergency room visits), this bias would be toward zero, and so we consider our set up to be a lower bound on the true effect. We establish our intuition for this setup with three thought experiments. First, imagine that all ED visits are 100% preventable with primary care. Then, to estimate the reduction in per capita ED visits results from a shock to primary care, one would assign 0 to those without an ED visit, and the number of visits to anyone with an ED visit.

[8] This issue is further mitigated in that the ACA expansion largely affected adults and did not change federal poverty level coverage thresholds for those aged 0 to 3.

Second, now imagine that some ED visits are 100% non-preventable. These visits should not be affected by the primary care shock, and so the individuals with only these visits should still be assigned a value of 0 for the outcome variable. (They could still be used for a falsification test.)

Finally, consider our actual situation in which certain diagnoses are sometimes preventable and sometimes not. We only care about the preventable parts for our primary estimate, and so in aggregate we can add up the preventable shares of each one to get the outcome variable.

We estimate the elasticity of substitution by comparing relative magnitudes of the effect of the Flint water contamination shock on ED visits and primary care visits relative to their respective means.

A final note is that the NYU ED algorithm is designed for the entire population, and not specifically for children. This is a known limitation of the algorithm, recognized by its developers (Billings, Parikh, Mijanovich 2000). However, lacking a child-specific algorithm, we consider this a valid starting point for our analysis.

A potential challenge to our identification is that the estimated differences could be attributed to the emergency management in Flint which began in December 2011, rather than the water contamination. To rule out the existence of trend in outcomes of interest prior to September 2015, as well as to explore its dynamics month-to-month, we estimate an extended form of specification (1) where the time period is disaggregated into monthly indicators:

$$Outcome_{ict} = a + \sum_j \beta_{1j} Flint * Month_{cj} + \beta_2 X_{ict} + \alpha_c + \delta_t + \varepsilon_{ict} \quad (2)$$

where $Flint * Month_{cj}$ is a monthly indicator for an individual residing in Flint, and β_{1j} estimates the difference in month j between Flint and control cities with respect to September 2015. We present estimates of β_{1j} only in graphical format.

Results

Before proceeding with the analysis, we use an event study specification to justify selection of September 2015 as the beginning of the treatment period. Figure 1 shows results for event study, showing differences in monthly lead tests for children born in Flint compared to control cities. Each point shows the difference in number of lead tests for children born Flint compared to control cities with respect to September 2015, with the 95% confidence interval around the estimate. The graph shows a clear rise in lead tests after September 2015, with a sharp peak between January and February 2016. The graph also shows no significant trend prior to September 2015, suggesting that despite ongoing speculation, the announcement of elevated residential tests by city authorities marked the beginning of the changing and mitigating behavior with respect to health care receipt for their children among residents in Flint.

Table 1 shows summary statistics and unadjusted difference-in-differences estimates. In Panel A, we see minimal changes in the demographic characteristics in our sample population. Following the information shock, receipt of any lead test more than doubles in Flint compared to a very small increase in comparison areas. The unadjusted difference-in-differences results show much more modest increases in every type of health care, except ED visits which we discuss in greater detail below. We also see an increase in payments in Flint compared to other cities. It is important to note that the after period (9/2015-2016) is much shorter than the lookback period (2013-9/2015). In Panel B, we find that ED visits that are non-preventable do not change, but we find decreases in all three of the preventable or non-emergent categories.

Main Results

Table 2 shows our primary differences-in-differences results. Using September 2015 as the treatment date (when the independent evidence of lead poisoning became public), the likelihood of receiving any lead test increased by 3.2 percentage points (pp), a 100% increase. We estimate a 1.1 pp increase in the share of individuals having any office visits, which is likely lower than the 3.2 pp increase in lead tests because many of these individuals were already seeing a provider. This increase in likelihood of office visits also raises vaccination rates by 0.77 pp, likely a spillover effect of receiving primary care for other services (Carpenter and Lawler Forthcoming). Interestingly, given our results below, we see no change in the share of children with an ED visit. This is possibly because ED visit is a heterogeneous measure including unclassified visits, which could be dampening the power of our analysis. Finally, we see an increase in average overall payments by $51 dollars per enrollee per month. This suggests that even if office visits are substituting for ED visits, they may be doing so at such a low rate that overall healthcare spending increases.

Table 3 contains results using the per capita measures of ED visits calculated using the method described above. We find no change in the number of non-preventable ED visits. For each of the other three types, our estimates indicate a decrease of about 1 visit per thousand enrollees per month, though the estimate for visits that were treatable in primary care is not statistically significant on its own. We create a composite metric by combining primary care preventable, primary care treatable, and non-emergent (defined as "Avoidable") which shows a strongly statistically significant decrease of 3.3 ED visits per thousand.

To test the sensitivity of our findings to the treatment period we estimated a flexible form specification, with two treatment periods – January to August 2015 and September 2015 to December 2016 – with qualitatively and quantitatively similar results, reported in Appendix C.

To further explore the substitution between ED and office care, we selected some of the most common Clinical Classification Software (CCS)[9] categories in the ED prior to September 2015. CCS categories were developed by the Healthcare Cost and Utilization Project of the Agency for Healthcare Research and Quality to classify ICD-9 diagnoses and procedures into clinically meaningful categories.

For this analysis, we identified the 10 most commonly occurring CCS categories in the ED corresponding to claims prior to September 2015 with diagnoses which the NYU algorithm classifies as entirely avoidable.[10] These CCS encompass over 86% of all avoidable claims in the ED. These CCS categories are listed in Table 4. We then aggregated claims to the person-month-CCS category, so that for each individual in our data, we have monthly use indicators, now split by CCS category. We excluded all individuals with no claims in the CCS in the month. As with the person-month analysis, we sum the NYU Algorithm indicators for preventable and non-preventable care in the ED. We re-estimate our specification for two venues of care: office visits (all diagnoses in each CCS), and ED (only avoidable shares as defined above).

We present results from this analysis in two formats. Figure 2 shows coefficient estimates by CCS category for any office visits (Panel A) and avoidable ED visits (Panel B). Table 5 then tests the hypothesis that in each CCS category the increase in office visits is

[9] https://www.hcup-us.ahrq.gov/toolssoftware/ccs/ccs.jsp

[10] For this classification, we limited claims to those with avoidable diagnoses, then identified the 10 most common CCS within that subsample of claims. We chose to focus on CCS because classifying diagnoses is too specific and not sufficiently informative. This also allows us to impute avoidability of CCS based on these most common diagnoses, but by including all diagnoses in a given CCS we avoid defining this category too narrowly.

mirrored in a decrease in avoidable ED visits. First looking at Figure 2, we see that in 6 of 9 CCS categories, office visits (Panel A) increase, with 5 of those 6 increases being statistically significant. Preventable ED visits (Panel B), on the other hand, decline in 6 of 9 categories. Comparing specific CCS categories, we particularly notice a sharp increase in office visits for skin and subcutaneous tissue infections, and a decrease in preventable ED visits. Abdominal pain is another category with a sharp increase in office visits and a decrease in preventable ED visits, as is gastritis and duodenitis. In Table 5 we present the results of a chi square test that compares the estimated change in office visits to that of preventable ED visits, (H_0: $\beta_{OfficeVisits} = -\beta_{AvoidableEDVisits}$), by CCS category. The chi square test fails to reject the null in any category, suggesting that, indeed, the increase in office visits is statistically indistinguishable from the decrease in preventable ED visits.

Mechanisms

To test the potential mechanisms for changing medical utilization, we use individuals episodes of care to explore choices in primary and ED care following the administration of lead test. Our main results suggest that the contamination has increased awareness of primary care through increased interaction with a physician or clinic. To examine this further, our analysis focuses on treatments received in the three months following a lead test to identify changing trends in utilization in Flint after September 2015.

We are interested in two types of trends: first, use of ED for treatment of top 10 CCS avoidable visits listed in Table 4; second, use of immunization, well visits, same provider, same clinic, and all avoidable ED visits. We report the results for top 10 CCS avoidable visits in Figure 3, where each point is the estimated difference-in-differences coefficient for Flint after September 2015 limited to visits to the ED in 3 months following a lead test. In this figure, the dependent variable is the abovementioned Avoidable composite metric interacted with the indicator for each of the CCS conditions. For each regression, the sample consists of fewer than 4,600 observations, making the estimates less precise. Nonetheless, we find statistically significant declines in epilepsy, gastrointestinal, and bronchitis avoidable visits, and non-significant declines in avoidable skin conditions and asthma.

The results of medical utilization in the post-lead test period are reported in Table 6. Here, the sample is limited to visits in the 3 month period following a lead test (columns (1)-(4)), and visits for patients with any lead tests (column (5)). We find statistically significant increases in likelihood of indicators of established care: 3.6pp increase in immunization, 2.9pp increase in well-visit, 8pp increase in seeing the same provider, 14.8pp increase in using the same clinic. The dependent variable in the last specification (column (5)) is the interaction of avoidable composite metric and indicator for any lead test by patient during the panel time. We find no significant change in avoidable visits for patients with lead test.

Pre-Trend Analysis

To test the validity of our specification, as well as to discern monthly trends of our analysis, we estimate the event study proposed equation (2). The estimates of β_{1j} are presented graphically in Figure 4; each point represents the difference in outcome between Flint and control cities relative to September 2015. Panel (A) shows results for number of claims, Panel (B) is any office visits, and Panel (C) reflect preventable ED visits. All three panels show that, despite seasonal variation, there is no discernable trend in these outcomes prior to September 2015, validating our use of difference-in-differences estimation method. Furthermore, we note a sustained increase in claims and office visits in the treatment period.

Discussion

The results in Table 2 show that definitive public information about the Flint water led to a 1.1 percentage point increase in those with office visits, which on a mean of 26.5% is an increase of 4.2%. From Table 3, column (6), we find a decrease of 3.3 visits per thousand, which on a mean of 61 per thousand represents a 5.4% decrease. Dividing the percent change in preventable ED visits by the percent change in office visits provides us with an estimate of elasticity of substitution between primary and ED care of about -1.3.

Figure 2 then breaks this result down by common diagnosis classifications that are often avoidable. In addition to our results not being driven by one or two conditions, we generally see a negative relationship between the magnitude of the effect on office visits for a particular condition and the magnitude of the effect on avoidable ED visits for that same condition. For upper respiratory infections, skin and subcutaneous tissue infections, abdominal pain and gastritis and duodenitis, we find precisely estimated and opposite effects. A chi-squared test of parity between the magnitudes of the estimated coefficients (H_0: $\beta_{OfficeVisits} = -\beta_{AvoidableEDVisits}$) yields statistically insignificant results suggesting we cannot reject the null that these estimates are of equal magnitude just oppositely signed. We urge caution in interpreting this test as it may lack specificity to reject our null hypothesis. However, this lends credence to our postulation that increased office visits are preventing avoidable ED visits.

Despite this substitution from potentially unnecessary ED visits to office visits, we also find a statistically significant increase in total Medicaid spending. We attribute this to relative frequency of each type of visits; given the vast difference in the share of enrollees with any ED visit (0.091) in a given month vs. any office visit (0.265), the absolute increase in office visits and associated testing costs more than the savings from prevented ED visits. However, the total

Medicaid spending amounts do not take into account that ED visits have other costs (e.g., stress, lost time, lost sleep, increased risk of complication, medical error, and infection) that may still make this substitution welfare improving. For this thought experiment, we assume that these other costs are larger for ED visits than for more common office visits.

Nevertheless, it is worth estimating the aggregate impact of healthcare costs following the water switch and comparing that to the proposed savings from the water switch. The 1.31 million enrollee months for the entire 2013-2016 data corresponds to 62,258 enrollees. Of those, approximately 3800 enrollees reside in Flint in the treatment period. Taking the $51/month coefficient from Table 2, and multiplying it by 3800 and by 12 months provides an estimate of about $2.3 million additional Medicaid spending per year.

Flint city officials estimated that the water switch could save the city $2.5 million a year.[11] This means that Michigan Medicaid alone spent more than 90% of the projected savings on Flint enrollees between the ages of 0 and 3. This does not include the future costs of any resulting health conditions, the current health costs of individuals above the age of 3, or productivity losses of the Flint labor force.

Future Work

Future analysis will include testing the impact of the information shock on the flow of eligible Medicaid patients enrolling in Medicaid. We will also incorporate CMS provider data to enable study of heterogeneity on the physician side. Finally, addition robustness checks will include starting treatment in January 2016, instead of September 2015, dropping managed care

[11] https://www.mlive.com/news/flint/index.ssf/2015/01/flints_dilemma_how_much_to_spe.html

patients for the estimates of the impact on costs, and limiting sample to the cohort of children born before April 2014 to avoid potential bias from endogenous fertility.

Conclusion

As the intensity of exposure to environmental pollutants decreases with improved regulation and control, health outcomes and subsequent treatments associated with them will decrease. This, however, does not negate the burden imposed by such contaminations on communities, as the anxiety and uncertainty associated with such exposure increase, among other things, utilization of all medical services. This paper contributes by identifying opportunities inherent when such environmental disasters increase awareness of health and health care.

Our findings show that residents of affected communities often turn to health care providers for guidance on appropriate response. Because the population studied here is low-income Medicaid-covered young children, our findings directly benefit communities and policymakers attempting to determine what to emphasize (e.g., education, screening, remediation) to counteract potential negative health effects of lead exposure in early childhood. In addition, to the extent that we find medically inefficient care, these results can provide additional information for physicians to address parental anxiety about the possible long-term effects of exposure to lead.

Furthermore, the Flint water switch led to increases in lead tests and associated office visits and gives us a unique opportunity to study the substitution between office visits and potentially unnecessary ED visits. While we find suggestive evidence of substitution, we do not find overall healthcare cost savings. Rather, health care costs in Flint increase. These results are specific to a cohort aged 0 to 3 years old. Thus, these results may not be generalizable to the general public.

We consider this to be a first step in conducting a long-term study of the effect of lead exposure in utero and in early childhood on health, education, and labor market outcomes. The results likely apply not only to Flint but also other cities with high lead levels (e.g., Providence, Philadelphia, Baltimore), while our elasticity of substitution results likely apply to any situation in which individuals are exogenously induced to seek care more often in primary care settings.

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Table 1: Summary Statistics

Panel A: Demographics and Primary Outcomes

	Before		After		Difference-in-Differences
	Flint	**Other**	**Flint**	**Other**	
Female	0.482	0.493	0.490	0.494	0.007
Black	0.610	0.533	0.618	0.536	0.0055
Any Lead Test	0.030	0.029	0.068	0.035	0.032
Any Office Visit	0.388	0.281	0.333	0.220	0.006
Any ED Visit	0.104	0.091	0.098	0.088	-0.0026
# of Claims	3.811	3.766	2.705	2.632	0.028
	(9.15)	(8.38)	(7.02)	(6.23)	
Payment	823.7	801.9	386.4	348.2	16.399
	(3388.9)	(3439.1)	(1976.6)	(2193.1)	
Person Months	58901	761826	35484	474037	
Persons	3698	51015	3867	53006	

Panel B: Per Capita Emergency Department Visits by Type

	Before		After		Difference in Differences
	Flint	**Other**	**Flint**	**Other**	
Non-Preventable	0.0093	0.0081	0.0083	0.007	0.0001
	(0.0676)	(0.0623)	(0.0616)	(0.0555)	
Preventable	0.0089	0.0061	0.0089	0.0073	-0.0012
	(0.0631)	(0.0547)	(0.633)	(0.063)	
Primary Care Treatable	0.0379	0.0294	0.0359	0.0285	-0.0011
	(0.1607)	(0.1386)	(0.1575)	(0.1365)	
Non-Emergent	0.0276	0.0248	0.0262	0.0245	-0.0011
	(0.1313)	(0.125)	(0.1289)	(0.1251)	
Person Months	58675	759650	35320	473119	
Persons	3684	50932	3852	52922	

Note: Standard deviation in parenthesis for non-dummy variables

Table 2: Individual Level Difference-in-Differences Results for all Enrolled Children

	(1) Any lead claims	(2) Any office visit	(3) Any vaccines	(4) Any ED visit	(5) # of claims	(6) Total payment ($)
Flint*After	0.032*** (0.001)	0.011*** (0.004)	0.0077*** (0.002)	-0.002 (0.001)	0.125*** (0.032)	51.056*** (17.205)
R-squared	0.007	0.061	0.027	0.007	0.041	0.037
Obs.	1,330,249	1,330,249	1,330,249	1,330,249	1,330,249	1,330,249
Number of enrollees	62,258	62,258	62,258	62,258	62,258	62,258
Number of Cities	16	16	16	16	16	16
Dependent Variable Mean	0.032	0.265	0.068	0.091	3.335	630.191

Notes: Regressions at the at the enrollee-month level, for all eligible, enrolled children. Treated city is Flint. Control cities are Ann Arbor, Dearborn, Detroit, Farmington Hills, Grand Rapids, Kalamazoo, Lansing, Livonia, Rochester Hills, Southfield, Sterling Heights, Troy, Warren, Westland, and Wyoming. Each coefficient is from a separate regression. All regressions include fixed effects for city, claim year, claim month, birth year, and birth month. Robust standard errors are clustered at city level. *** p<0.01, ** p<0.05, * p<0.1

Table 3: Changes in Per Capita ED Visits by Type

	(1) Non-Preventable	(2) Preventable	(3) Primary Care Treatable	(4) Non-Emergent	(5) PC Sensitive	(6) Avoidable
Flint*After	0.0003	-0.0013***	-0.0010	-0.0010***	-0.0020**	- 0.0033***
	(0.0003)	(0.0002)	(0.0009)	(0.0004)	(0.0009)	(0.0008)
R-squared	0.004	0.003	0.007	0.005	0.008	0.008
Obs.	1,326,764	1,326,764	1,326,764	1,326,764	1,326,764	1,326,764
Number of enrollees	67,167	67,167	67,167	67,167	67,167	67,167
Number of Cities	16	16	16	16	16	16
Dependent Variable Mean	0.0078	0.0067	0.0296	0.0249	0.0545	0.0613

Notes: Primary Care (PC) Sensitive visits include PC Treatable and Non-Emergent; Avoidable visits include Preventable, PC Treatable, and Non-Emergent. Regressions at the at the enrollee-month level, for all eligible, enrolled children. Treated city is Flint. Control cities are Ann Arbor, Dearborn, Detroit, Farmington Hills, Grand Rapids, Kalamazoo, Lansing, Livonia, Rochester Hills, Southfield, Sterling Heights, Troy, Warren, Westland, and Wyoming. Each coefficient is from a separate regression. All regressions include fixed effects for city, claim year, claim month, birth year, and birth month. Robust standard errors are clustered at city level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4: Top CCS Categories for Avoidable Claims in the ED

CCS	Description	% of Claims
126	Upper Respiratory Infection (URI)	48.51
133	Lower Respiratory Infection (LRI)	10.83
197	Skin and Subcutaneous Tissue Infection	7.16
128	Asthma	6.81
251	Abdominal Pain	3.65
83	Epilepsy; convulsions	3.82
222	Hemolytic Jaundice and Perinatal Jaundice	1.74
140	Gastritis and Duodenitis	1.39
107	Cardiac Arrest and Ventricular Fibrillation	1.28
125	Acute Bronchitis	1.25

Notes: Top 10 most frequently occurring CCS categories in claims for care identified as avoidable by the NYU Algorithm taking place in the ED prior to September 2015.

Table 5: Effect comparison of substitution between office visits and avoidable ED visits by category of care.

Description	**Any Office Visits**		**Avoidable ED Visits**		**H_0**	
	Coeff	Std. Err	Coeff.	Std. Err	Chi2	p>Chi2
All	0.027	0. 004	-0.003	0. 001	0.020	0.886
Upper Respiratory Infection (URI)	0.017	0.008	-0.044	0.014	0.030	0.852
Lower Respiratory Infection (LRI)	-0.027	0.012	0.007	0.016	0.050	0.831
Skin and Subcutaneous Tissue Infection	0.086	0.015	-0.036	0.012	0.220	0.636
Asthma	0.002	0.016	-0.031	0.014	0.020	0.877
Abdominal Pain	0.168	0.027	-0.086	0.024	0.110	0.743
Epilepsy; convulsions	-0.078	0.018	-0.001	0.020	0.060	0.811
Jaundice	0.058	0.024	-0.007	0.003	0.280	0.596
Gastritis and Duodenitis	0.100	0.024	-0.095	0.008	0.000	0.968
Acute Bronchitis	-0.020	0.010	-0.003	0.005	0.020	0.902

Note: H_0: $\beta_{OfficeVisits} = -\beta_{AvoidableEDVisits}$. Each estimate comes from a separate regression at the at the enrollee-month level, for all children with claims in the specified CCS category. Treated city is Flint. Control cities are Ann Arbor, Dearborn, Detroit, Farmington Hills, Grand Rapids, Kalamazoo, Lansing, Livonia, Rochester Hills, Southfield, Sterling Heights, Troy, Warren, Westland, and Wyoming. All regressions include fixed effects for city, claim year, claim month, birth year, and birth month. Robust standard errors are clustered at city level.

Table 6: Use of primary care following lead testing

	(1) Immunization	(2) Well	(3) Same Provider	(4) Same Clinic	(5) Avoidable ED
Flint*After	0.0367*	0.0294***	0.0802**	0.1480***	0.0021
	(0.0148)	(0.0050)	(0.0231)	(0.0295)	(0.0023)
R-squared	0.0252	0.0242	0.24	0.3463	0.0101
Obs.	21413	21413	16820	16820	687742
Number of Cities	16	16	16	16	16
Dependent Variable Mean	0.1668	0.2004	0.5383	0.6272	0.0294

Note: Each column shows estimates for specification for care received within 91 days of a lead test. The dependent variables are: Immunization – immunization as primary reason for visit (CCS code 10); Well – well child visit (CCS code 255 and 256); Same provider – provider seen was the same (National Provider Identifier) as the one administering the lead test; Same clinic – clinic was the same (National Biller Identifier) as in the one billing for lead test ; Avoidable ED – composite of primary care sensitive care interacted with indicator for any lead test during panel time. Specifications (1)-(4) limit observations to visits within 91 days of administration of lead test. Treated city is Flint. Control cities are Ann Arbor, Dearborn, Detroit, Farmington Hills, Grand Rapids, Kalamazoo, Lansing, Livonia, Rochester Hills, Southfield, Sterling Heights, Troy, Warren, Westland, and Wyoming. All regressions control for female, maternal race and education, and include fixed effects for city, month, year, birth year, and birth month. Robust standard errors are clustered at city level.

Figure 1 Number of Lead Tests in Flint Compared to Control Cities

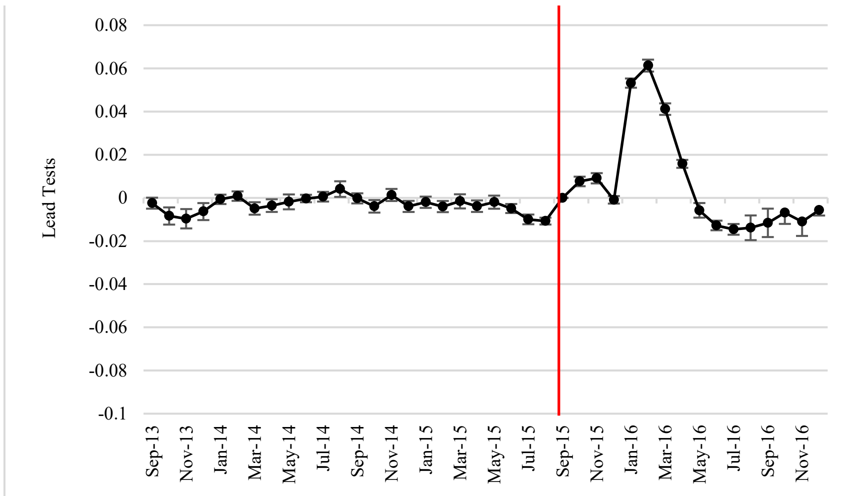
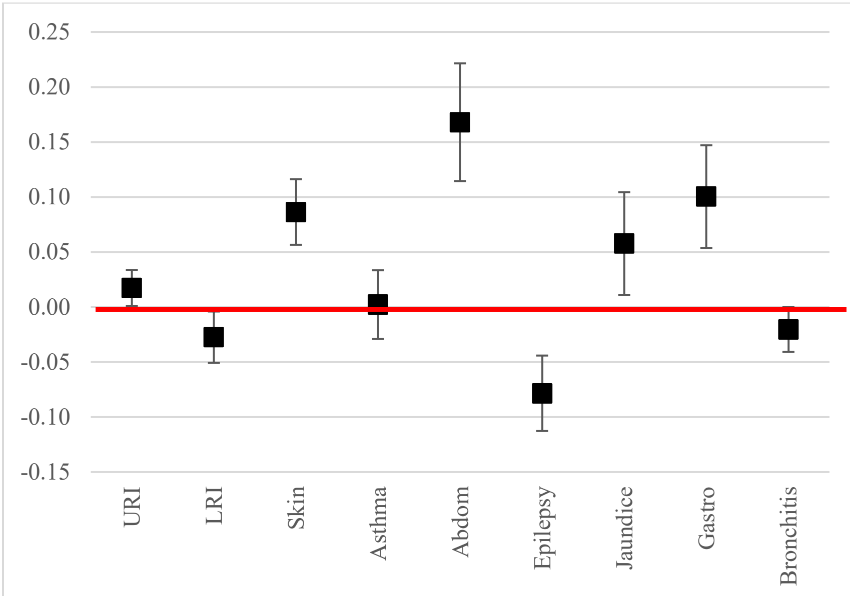
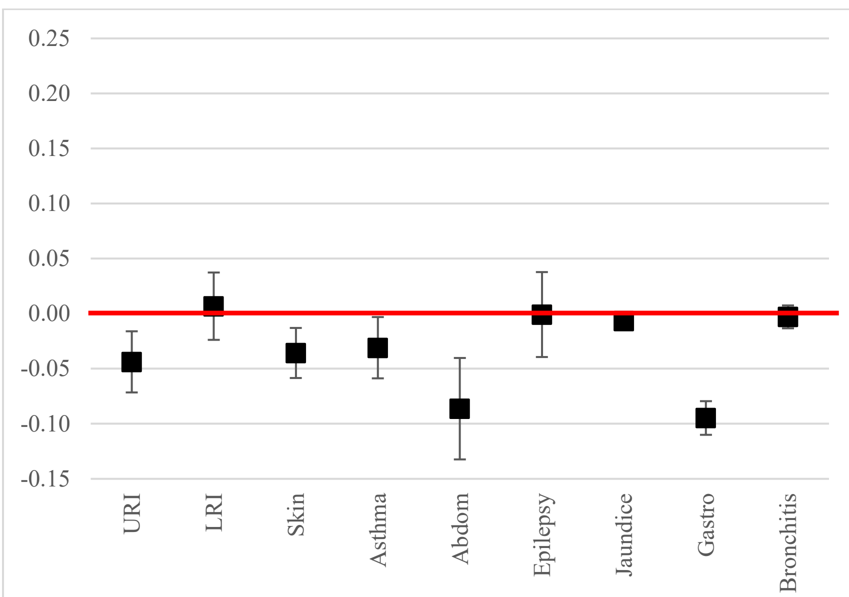


Figure 2: Changes in Outcome by Diagnosis Classification

Panel A: Any Office Visits

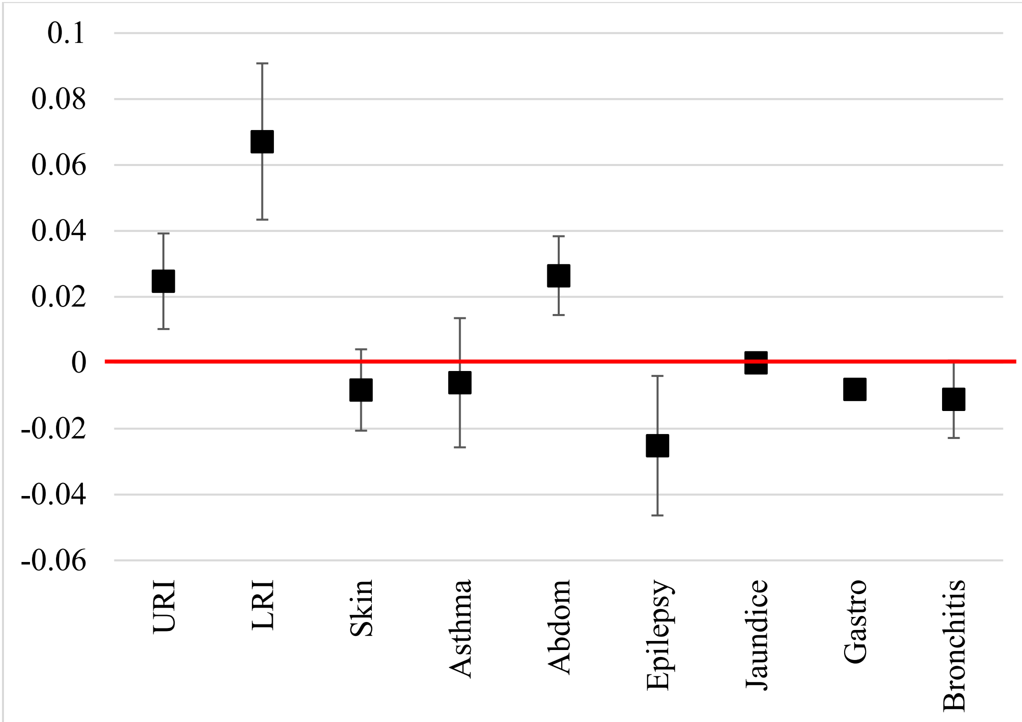


Panel B: Per Capita Avoidable ED Visits



Notes: Each point is the estimate of a separate specification at the at the enrollee-month level, for all children with claims in the specified CCS category. Treated city is Flint. Control cities are Ann Arbor, Dearborn, Detroit, Farmington Hills, Grand Rapids, Kalamazoo, Lansing, Livonia, Rochester Hills, Southfield, Sterling Heights, Troy, Warren, Westland, and Wyoming. All regressions include fixed effects for city, claim year, claim month, birth year, and birth month. Robust standard errors are clustered at city level. Whiskers show a 95% confidence interval.

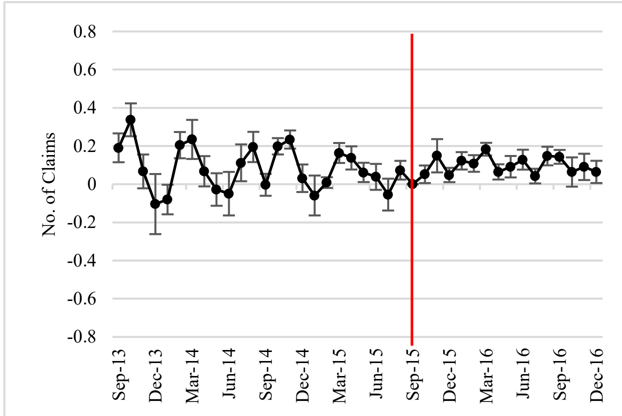
Figure 3: Use avoidable ED visits for top 10 preventable CCS following lead testing



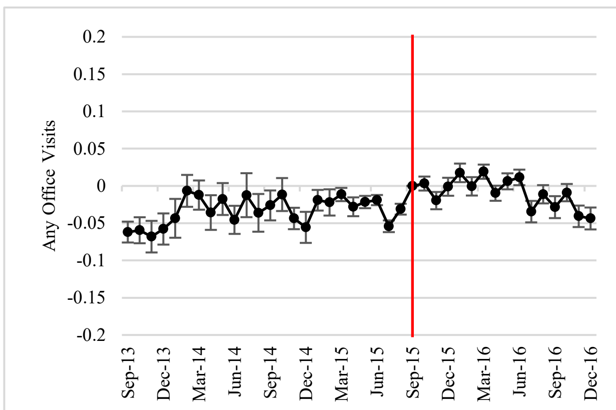
Note: Each point is the estimate of a separate specification at the visit level limited to all ED visits within 91 days of administration of a lead test. The dependent variable is an interaction of the composite of avoidable primary care sensitive care interacted with indicated CCS condition. There were no observations of jaundice in selected subsample. Treated city is Flint. Control cities are Ann Arbor, Dearborn, Detroit, Farmington Hills, Grand Rapids, Kalamazoo, Lansing, Livonia, Rochester Hills, Southfield, Sterling Heights, Troy, Warren, Westland, and Wyoming. All regressions control for female, maternal race and education, and include fixed effects for city, month, year, birth year, and birth month. Robust standard errors are clustered at city level. Whiskers show a 95% confidence interval.

Figure 4: Adjusted Monthly Differences by Outcome

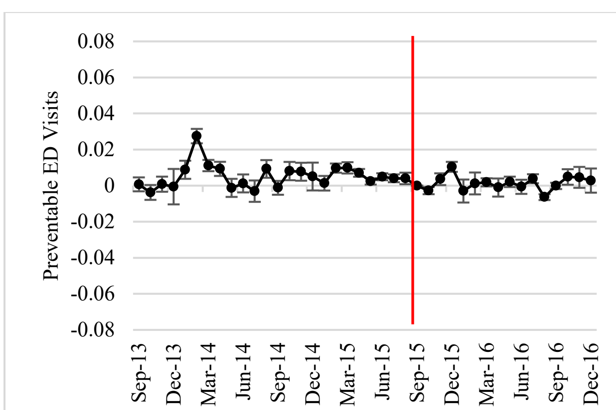
Panel A: Number of Claims



Panel B: Any Office Visits



Panel C: Preventable ED visit



Notes: Each graph represents estimation results from a separate specification. Each point represents the monthly difference between treated and control, adjusted for gender, maternal race, and maternal education. Treated city is Flint. Control cities are Ann Arbor, Dearborn, Detroit, Farmington Hills, Grand Rapids, Kalamazoo, Lansing, Livonia, Rochester Hills, Southfield, Sterling Heights, Troy, Warren, Westland, and Wyoming. All regressions include fixed effects for city, birth year, and birth month. Robust standard errors are clustered at city level. Whiskers show a 95% confidence interval.

Appendix A. Background on Flint (adapted from Grossman and Slusky 2019)

Until 1967, Flint used the Flint River as a water source. The city had shortage concerns given its expanding population (Carmody 2016), and so began drawing water from Lake Huron through the Detroit Water and Sewerage Deparment (DWSD). In 2011, the Governor of Michigan appointed an Emergency Manager for the city to make fiscal decisions, given the city's precarious economic health (Longley 2011). At this time, DWSD water rates were rising (Zahran, McElmurry, and Sadler 2017). To avoid these higher rates, the Emergency Manager explored building a pipeline directly to Lake Huron (City of Flint 2015; Walsh 2014). However, the project would take more than two years to complete. In the interim, Flint would use water from the Flint River (beginning in April 2014), while Genesee County continued to work with DWSD (Carmody 2016).

Flint had to treat the new water source, but did not use anti-corrosive inhibitors (Pieper et al. 2017; Olson et al. 2017). Flint citizens were concerned about the appearance and odor of the water but were repeatedly assured that it was safe to drink (City of Flint 2015a,b). While the city issued multiple boil advisories due to a positive fecal coliform tests and an EPA violation for excess trihalomethanes (TTHM) in the water (Fonger 2014a, 2014b; Adams 2014), Flint consistently reassured citizens the water was safe and that any issues would be fixed soon (City of Flint 2015a,b).

In the summer of 2015, a team led by Mark Edwards began independently testing Flint's water and in August reported much higher levels of lead than previously reported, due to extremely corrosive water (http://flintwaterstudy.org/wp-content/uploads/2015/10/Flint-Corrosion-Presentation-final.pdf). Mona Hanna-Attish, a Flint pediatrician, in September, 2015 reported a substantial increase in blood lead levels in children (Fonger 2015c; Hanna-Attish et al.

2016). This finally led the city to switch back to Lake Huron water on October 16, 2015 (Emery 2015).

Appendix Figure A1: Timeline of Important Events in Flint

1897: Flint passes ordinance that all connections with any water main be made with lead pipes (Masten et al. 2016)	1967-2014: Flint receives water from Detroit Water and Sewerage Department (DWSD)	2011: Governor appoints Emergency Manager	2009-2013: Water rates (prices) consistently increase	March 2014: Flint and Genesee County plan own pipeline to Lake Huron	April 2014: Flint changes water source to Flint River, Genesee County stays with DWSD	Aug – Sept 2014: Positive test for fecal coliform, first boil advisory
Oct 2014: Flint GM plant switches off Flint water supply because of engine corrosion.	Jan – Mar 2015: Emergency manager stresses water is safe, refuses to return to DWSD	Jun – Jul 2015: Dr. Edwards independently tests Flint water lead levels, 19 times more corrosive than DWSD.	Sept 2015: Dr. Hanna-Attisha holds press conference announcing increased rates of child blood lead levels.	Oct 2015: Flint stops receiving water from Flint River.	Jan 2016: Michigan Governor apologizes on national television	

Source: Adapted from Grossman and Slusky (2019)

Appendix B: Results with "patched" NYU Algorithm

Using Johnson et al. (2017) classification of uncategorized visits, we re-estimated specification (1) for ED visits. Results are presented in Table B1; though the significance of most estimates is lost, and the magnitudes are attenuated, the sign is consistent with our main results. We choose not to use this "patch" because the new classifications are not validated.

Table B1: Changes in Per Capita ED Visits by Type

	(1)	(2)	(3)	(4)	(5)	(6)
	Non-Preventable	Preventable	Primary Care Treatable	Non-Emergent	PC Sensitive	Avoidable
Flint*After	0.0000 (0.0005)	-0.001*** (0.0001)	-0.0006 (0.0009)	-0.0006 (0.0004)	-0.0012 (0.0013)	-0.0022* (0.0012)
R-squared	0.0051	0.0027	0.0079	0.0056	0.0089	0.0088
Obs.	1,326,764	1,326,764	1,326,764	1,326,764	1,326,764	1,326,764
Number of enrollees	67,167	67,167	67,167	67,167	67,167	67,167
Number of Cities	16	16	16	16	16	16
Dependent Variable Mean	0.0121	0.0072	0.037	0.029	0.066	0.0738

Notes: Primary Care (PC) Sensitive visits include PC Treatable and Non-Emergent; Avoidable visits include Preventable, PC Treatable, and Non-Emergent. Regressions at the at the enrollee-month level, for all eligible, enrolled children. Treated city is Flint. Control cities are Ann Arbor, Dearborn, Detroit, Farmington Hills, Grand Rapids, Kalamazoo, Lansing, Livonia, Rochester Hills, Southfield, Sterling Heights, Troy, Warren, Westland, and Wyoming. Each coefficient is from a separate regression. All regressions include fixed effects for city, claim year, claim month, birth year, and birth month. Robust standard errors are clustered at city level. *** p<0.01, ** p<0.05, * p<0.1

Appendix C: Flexible form time indicator

Table C1: Individual Level Difference-in-Differences Results for all Enrolled Children

	(1) Any lead claims	(2) Any office visit	(3) Any vaccines	(4) Any ED visit	(5) # of claims	(6) Total payment ($)
Flint*Jan '15	-0.0031***	-0.0022	-0.0016	0.0015	-0.1813***	-22.66
	(0.0006)	(0.0061)	(0.0029)	(0.0024)	(0.0337)	(13.29)
Flint*Sept '15	0.0304***	0.0104	0.0070**	-0.0016	0.0513	42.86*
	(0.0008)	(0.0063)	(0.0030)	(0.0022)	(0.0429)	(21.02)
R-squared	0.0072	0.0683	0.027	0.0098	0.041	0.0374
F-Test	1703.3	7.1	15.8	8.7	62.6	29.7
Obs.	1,330,177	1,330,177	1,330,177	1,330,177	1,330,177	1,330,177
Number of Cities	16	16	16	16	16	16
Dependent Variable Mean	0.0328	0.0266	0.0685	0.091	3.336	630.191

Notes: *Flint*Jan '15* indicates enrollee-month observations in Flint between January and August 2015. *Flint*Sept '15* indicates enrollee-month observations in Flint between September 2015 and December 2016. F-statistic of joint significance of DiD coefficients reported. Regressions at the at the enrollee-month level, for all eligible, enrolled children. Treated city is Flint. Control cities are Ann Arbor, Dearborn, Detroit, Farmington Hills, Grand Rapids, Kalamazoo, Lansing, Livonia, Rochester Hills, Southfield, Sterling Heights, Troy, Warren, Westland, and Wyoming. Each coefficient is from a separate regression. All regressions include fixed effects for city, claim year, claim month, birth year, and birth month. Robust standard errors are clustered at city level. *** p<0.01, ** p<0.05, * p<0.1

Table C2: Changes in Per Capita ED Visits by Type

	(1)	(2)	(3)	(4)	(5)	(6)
	Non-Preventable	Preventable	Primary Care Treatable	Non-Emergent	PC Sensitive	Avoidable
Flint*Jan '15	0.0005**	-0.0005	-0.0029	0.0023***	-0.0006	-0.0012
	(0.0001)	(0.0003)	(0.0018	(0.0004)	(0.0023)	(0.0026)
Flint*Sept '15	0.0004	-0.0015***	-0.0022	-0.0001	-0.0023	-0.0039**
	(0.0003)	(0.0001)	(0.0016)	(0.0004)	(0.0017)	(0.0017)
R-squared	0.004	0.003	0.0068	0.0052	0.008	0.0082
F-Test	9.04	48.81	1.58	13.79	6.84	19.59
Obs.	1,330,177	1,330,177	1,330,177	1,330,177	1,330,177	1,330,177
Number of Cities	16	16	16	16	16	16
Dependent Variable Mean	0.0077	0.0067	0.0295	0.0248	0.0544	0.0611

Notes: *Flint*Jan '15* indicates enrollee-month observations in Flint between January and August 2015. *Flint*Sept '15* indicates enrollee-month observations in Flint between September 2015 and December 2016. F-statistic of joint significance of DiD coefficients reported. Dependent variables: Primary Care (PC) Sensitive visits include PC Treatable and Non-Emergent; Avoidable visits include Preventable, PC Treatable, and Non-Emergent. Regressions at the at the enrollee-month level, for all eligible, enrolled children. Treated city is Flint. Control cities are Ann Arbor, Dearborn, Detroit, Farmington Hills, Grand Rapids, Kalamazoo, Lansing, Livonia, Rochester Hills, Southfield, Sterling Heights, Troy, Warren, Westland, and Wyoming. Each coefficient is from a separate regression. All regressions include fixed effects for city, claim year, claim month, birth year, and birth month. Robust standard errors are clustered at city level. *** p<0.01, ** p<0.05, * p<0.1