The Effects of Fuel Subsidies on Air Quality: Evidence from the Iranian Subsidy Reform*

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Abstract

Gasoline taxes have been touted by many economists as an efficient and relatively simple tool to address environmental concerns and other problems associated with gasoline consumption. Nevertheless, rather than removing subsidies and increasing gasoline taxes, many countries still subsidize gasoline, which may have the opposite effect of exacerbating air pollution. As a result of its large energy subsidies and artificially low national energy prices, Iran is one of the most energy-intensive countries in the world. Iran's capital city, Tehran, is also amongst the most polluted cities in the world. The Iranian government has recently taken a series of measures to reform and cut back on its energy subsidies. In this paper, we evaluate the effects of the Iranian subsidy reform on air quality using a regression discontinuity design. Our results provide evidence across multiple different empirical specifications that the subsidy reform in Iran, particularly subsidy reforms that both increased energy prices and restricted gasoline consumption, led to improvements in air quality. In contrast, subsidy reforms that increased fuel prices but did not also restrict gasoline consumption were less effective in reducing air pollution.

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1 Introduction

Gasoline consumption is an important source of air pollution and a major environmental concern in urban areas (Lin and Prince, 2009; Lin Lawell, 2017). Motor vehicles are the primary source of carbon monoxide (CO), and an important source of volatile organic compounds and nitrogen oxides (which include nitrogen dioxide (NO_2)) responsible for the formation of photochemical smog and ground-level ozone (O_3). Vehicular emissions also contribute to the ambient air concentrations of particulate matter (PM_{10}) (U.S. Environmental Protection Agency, 1994; Zhang et al., 2017; Beaudoin and Lin Lawell, 2022).

Gasoline taxes have been touted by many economists as an efficient and relatively simple tool to address environmental concerns and other problems associated with gasoline consumption. Nevertheless, rather than removing subsidies and increasing gasoline taxes, many countries still subsidize gasoline (Lin Lawell, 2017). The global mean gasoline tax fell by 13.3 percent from 2003 to 2015, due in part to a shift in consumption towards countries that have gasoline subsidies (Ross et al., 2017). Post-tax fossil fuel subsidies reached a staggering $5.3 trillion worldwide in 2015, representing 6.5% of global GDP (Coady et al., 2017). There is pervasive mispricing of energy across developed and developing countries alike (Parry et al., 2014). Oil-rich countries in the Middle East and North Africa have the highest gasoline subsidies (Ross et al., 2017).

The prevalence of gasoline subsidies worldwide and the fall in the global mean gasoline tax may exacerbate air pollution and other problems associated with gasoline consumption. Nevertheless, the effects of gasoline subsidies on air quality, and the effects of gasoline subsidies on different air pollutants, remain open empirical questions that heretofore have not been fully addressed in the previous literature, particularly for oil-rich countries in the Middle East and North Africa that have the highest gasoline subsidies.

The Iranian government has heavily subsidized petroleum products since the early 1980s. As a result of these energy subsidies and artificially low national energy prices, Iran is one of the most energy-intensive countries in the world. Iran's capital city, Tehran, is also amongst the most polluted cities in the world (Heger and Sarraf, 2018). The Iranian government has recently taken a series of measures to reform and cut back on its energy subsidies. In this paper, we evaluate the effects of the Iranian subsidy reform on air quality using a regression discontinuity design.

Our results provide evidence across multiple different empirical specifications that the subsidy reform in Iran, particularly subsidy reforms that both increased energy prices and restricted gasoline consumption, led to improvements in air quality. In contrast, subsidy reforms that increased fuel prices but did not also restrict gasoline consumption were less effective in reducing air pollution.

The balance of our paper proceeds as follows. Section 2 reviews the previous literature. Section 3 provides background information about air pollution in Iran, energy subsidies in Iran, and the Iranian subsidy reform. We describe our data in Section 4. We present our conceptual framework and regression discontinuity design in Section 5. We present our empirical results in Section 6. We discuss our results and conclude in Section 7.

2 Previous Literature

2.1 Fossil Fuel Subsidies

One strand of literature upon which we build is the literature on fossil fuel subsidies. Using detailed measurements of net gasoline taxes and subsidies, Ross et al. (2017) find that 33 countries subsidized gasoline for at least one 12-month period from 2003 to 2015, and 9 countries subsidized gasoline for the entire period. Countries that are economically dependent on oil and gas exports tend to be the ones that subsidize gasoline, perhaps due to political pressure to distribute resource revenues. Oil-rich countries in the Middle East and North Africa have the highest net subsidies (Ross et al., 2017). Balke et al. (2015) identify 24 oil-producing countries with fuel subsidies, and find that their retail fuel prices are only about 34 percent of the world price. Post-tax fossil fuel subsidies reached a staggering $5.3 trillion worldwide in 2015, representing 6.5% of global GDP (Coady et al., 2017).

Pricing energy below cost is inefficient as it leads to the overconsumption of fossil fuels and causes deadweight loss. Davis (2014) estimates that, under certain assumptions about supply and demand elasticities, the annual deadweight loss caused by fuel subsidies worldwide was over $44 billion in 2012. In addition to deadweight loss, there are other distortions caused by pricing energy below cost – including smuggling, black-market transactions, and other socially wasteful activities; the environmental damages caused by fossil fuel overconsumption; and the accident and congestion externalities from transportation fuel consumption – all of which further increase the social costs of energy subsidies (Gürer and Ban, 2000; Lin and Prince, 2009; Lin and Zeng, 2014; Lin Lawell, 2017; Ferraresi et al., 2018; Adetutu and Weyman-Jones, 2019). In their analysis of more than 150 countries, Parry et al. (2014) find that there is pervasive mispricing of energy across developed and developing countries alike, and that implementing efficient energy prices instead would reduce fossil-fuel air pollution deaths by 63 percent. Davis (2017) estimates that global fuel subsidies cause $7 billion in external costs annually from local air pollution.

Previous studies of the effects of energy subsidies have focused primarily on the effects of energy subsidies and energy subsidy reform on energy consumption, energy production, markets, GDP, and welfare. Hahn and Metcalfe (2021) examine the efficiency and equity impacts of the California Alternate Rates for Energy (CARE), a large energy subsidy that provides a price reduction for low-income consumers of natural gas and electricity, and find that the natural gas subsidy appears to reduce welfare. Zhao et al. (2019) use an economic optimization model to simulate the effects of phasing out producer subsidies in U.S. federal and state regulation on optimal oil and gas production. Aldy (2013) argues that the elimination of subsidies for U.S. fossil fuel production could provide meaningful deficit reduction benefits without increasing energy prices, adversely impacting U.S. energy security, or undermining job creation; and may lead to potentially lower global fuel prices by providing the United States with increased leverage in negotiations over eliminating fossil fuel subsidies in the developing world. Aune et al. (2017) examine the oil market impacts and welfare effects of subsidy removal in OPEC and non-OECD countries. BuShehri and Wohlgenant (2002) use a partial equilibrium model to measure the welfare implications of a reduction in electricity subsidies in Kuwait. Gelan (2018) conducts a simulation experiment to study the effects of removing energy subsidies on prices and GDP in Kuwait. Abdallah Mostafa (2021) analyzes the impact of energy subsidy reform on economic growth in Egypt. Ghosh (2022) analyzes the impact of India's diesel subsidy reforms and pricing policy on growth and inflation. Fuje (2019) uses a time regression discontinuity design to analyze the Ethiopian fossil fuel subsidy reform program, and finds that the removal of fossil fuel subsidies results in higher grain price dispersion which could in turn have heterogeneous welfare effects on different districts in Ethiopia depending on the district's relative share of income from grains. Hartley and Medlock (2008) find that forcing a national oil company to subsidize domestic consumers shifts oil production from the future toward the present, resulting in greater employment in the initial time periods. Salehi-Isfahani (1996) analyzes government subsidies and the demand for petroleum products in Iran. Ghoddusi et al. (2022) study the effect of fuel subsidy reform on the behavior of gasoline consumers using three major fuel subsidy reform events in Iran, and find a consistent decline in the gasoline price elasticity following each subsidy reform event.

Previous analyses of the effects of energy subsidies on air pollution are primarily based on models. For example, to quantify the effects of energy price subsidies on local air pollution, the World Bank recommends first analyzing the effect of consumer price subsidies on levels and patterns of energy consumption using sector-specific own-price and cross-price elasticities of energy demand, power sector models, sector models, country-specific computable general equilibrium (CGE) models, and models for road transport sector or motor vehicle fleets; and then estimating the impacts of energy consumption on emissions using fuel- and sector-specific emission factors for fuels and sectors impacted by price subsidies (Enriquez et al., 2018). Haqiqi and Manzoor (2012) analyze the effects of phasing out energy subsidies on air polluion using a a multi-pollutant, multi-fuel and multi-sector computable general equilibrium (CGE) model.

We build on the previous literature on fossil fuel subsidies by empirically examining their effects on air pollution. The effects of fuel subsidies on air quality, and the effects of fuel subsidies on different air pollutants, remain open empirical questions that heretofore have not been fully addressed in the previous literature, particularly for oil-rich countries in the Middle East and North Africa that have the highest gasoline subsidies.

2.2 Energy and Iran

In addition to the literature on fossil fuel subsidies, we also build upon the literature on energy in Iran. Ghandi and Lin (2012) model the dynamically optimal oil production on Iran's offshore Soroosh and Nowrooz fields, which have been developed by Shell Exploration through a buy-back service contract. Ghandi and Lin Lawell (2017) analyze the rate of return and risk factors to international oil companies in Iran's buy-back service contracts. Ghoddusi et al. (2018) estimate the price elasticity of gasoline smuggling in Iran, and find that the foreign-to-home gasoline price ratios have a significant effect on the elasticity of demand. Farzanegan and Krieger (2018) study the short- and long-run responses of income inequality to positive per capita oil and gas rent shocks in Iran, and find a positive and statistically significant response of income inequality to oil rent booms within four years of the shock. Aghaei and Lin Lawell (2022) examine the relationships among energy consumption, economic growth, inequality, and poverty in Iran. Rezagholizadeh et al. (2022) examine the factors that affect stock returns in the Tehran Stock Exchange, the largest stock exchange in Iran, and find that oil price risk coefficients for the top five energy consuming industries are higher than for the top ten industries by market cap. We build on the previous literature on energy in Iran by examining the effects of Iran's energy subsidies on air pollution.

3 Background

3.1 Air Pollution in Iran

The air in Tehran, the capital of the Islamic Republic of Iran (IRI), is amongst the most polluted in the world (Heger and Sarraf, 2018). There are more than 17 million vehicular trips per day in Tehran (Hosseini and Shahbazi, 2016), and many of the vehicles have outdated technology (Heger and Sarraf, 2018). Rapid population growth, industrial development, urbanization, and increasing fuel consumption make reducing air pollution in Tehran difficult (Heger and Sarraf, 2018).

Tehran's air pollution problem is further exacerbated by its topography and climate. Tehran is at a high altitude and is surrounded by the Alborz Mountain Range, which traps polluted air. Moreover, temperature inversion, a phenomenon particularly occurring during the winter months, prevents air pollutants from being diluted (Heger and Sarraf, 2018).

In Tehran, motor vehicle emissions are major sources of CO, O_3, NO_2, and PM_{10} (Zerbonia and Soraya, 1978; Azarmi and Arhami, 2017; Heger and Sarraf, 2018). It has been estimated that vehicles are responsible for 85 percent of Tehran's emissions of nitrogen oxides (which include NO_2); over 90 percent of its hydrocarbon and carbon monoxide (CO) emissions (Zerbonia and Soraya, 1978); 70 percent of its particulate matter emissions (Heger and Sarraf, 2018); and approximately 80 percent of its emissions of nitrogen oxides (which include NO_2), PM_{10}, and CO (Azarmi and Arhami, 2017). As for emissions of particulate matter, vehicles are responsible for 70 percent of Tehran's particulate matter emissions; power plants and refineries are responsible for about 20 percent; industrial sources and gas terminals emit 8 percent; and households and commercial sources are responsible for the remaining 2 percent (Heger and Sarraf, 2018). Since motor vehicle emissions are major sources of CO, O_3, NO_2, and PM_{10} in Tehran (Zerbonia and Soraya, 1978; Azarmi and Arhami, 2017; Heger and Sarraf, 2018), we analyze the effects of the Iranian subsidy reform on CO, O_3, NO_2, and PM_{10}.

Motor vehicle emissions are not a primary source of sulfur dioxide (SO_2) in Tehran (Massoudi, 1977) or elsewhere (Zhang et al., 2017). Instead, industrial sources, domestic and commercial heating are responsible for nearly all the SO_2 emissions in Tehran (Massoudi, 1977). Thus, since SO_2 may be more related to industrial activity than to driving behavior (Zhang et al., 2017), we include SO_2 as a control variable in order to control for any changes in industrial activity that may have been correlated with the energy subsidy reform events.

3.2 Energy Subsidies in Iran

In Iran, domestic energy prices, including gasoline prices, are set administratively rather than by the market. The Iranian government has heavily subsidized petroleum products, utilities, as well as a few food products since the early 1980s. These subsidies were originally introduced to manage the economic challenges during the war against Iraq. As seen in Figure A-1 in Appendix A, Iran had the highest pre-tax energy subsidies (including subsidies on petroleum, electricity, natural gas, and coal) as a percentage of GDP amongst 19 countries in the Middle East and North Africa in 2011 (Sdralevich et al., 2014). Iran's overall indirect subsidies in 2007-2008 have been estimated to total $77.2 billion, about 27 percent of the country's GDP (World Bank, 2016). Prior to the recent subsidy reforms, an average Iranian household of four received about $4,000 annually in various subsidies on oil and natural gas alone (Guillaume et al., 2011). Over the last four decades, energy prices in Iran have changed only a handful of times, each time after remaining constant for a long period (Kheiravar, 2019). As a result of these energy subsidies and artificially low national energy prices, Iran is one of the most energy-intensive countries in the world.

Iran's high fuel subsidies have made subsidized fuel in Iran very inexpensive, leading not only to high energy consumption, but also to lucrative opportunities for smuggling fuel into neighboring markets and other countries (Ghoddusi et al., 2018; Khajehpour, 2018). Moreover, although redistributing wealth and helping the poor are among the primary reasons for Iran's energy subsidies, energy subsidies do not lead to the intended wealth redistribution, as the benefits go mainly to the wealthy (Kheiravar, 2019).

3.3 Iranian Subsidy Reform

The Iranian government has recently taken a series of measures to reform and cut back on its energy subsidies. The first subsidy reform event took place on June 27, 2007. As part of the first subsidy reform event, the government announced a price hike for gasoline and, in order to control fuel smuggling activities (Khajehpour, 2018), also introduced a 60 liter monthly gasoline consumption quota for each vehicle. The monthly gasoline consumption quota was implemented via a fuel card that was issued for each vehicle owner. The 60 liter monthly quota (with roll over) was for gasoline and premium gasoline only: each fuel card owner could buy up to 60 liters of gasoline or premium gasoline per month at the subsidized price. To buy gasoline exceeding the 60 liter quota, one had to pay a significantly higher price; this price hike was another component of the first subsidy reform event. In particular, after the first subsidy reform event on June 27, 2007, a fuel card holder could buy up to 60 liters of gasoline at 1000 IRR (100 Iranian Toman[1]) per liter, and once the 60 liter quota is reached they had to pay 4000 IRR (400 Toman) per liter (Kheiravar, 2019). The first subsidy reform therefore implemented a two-tiered consumption system, with a low ration at a lower price and less restricted availability of fuel at a higher price (Khajehpour, 2018).

The second subsidy reform event took place on December 18, 2010, when the Iranian government implemented the first phase of the Iranian subsidy reform plan, announcing a significant increase in energy prices as well as in the prices of subsidized agricultural products by up to 20 times. Under this plan, the government removed an estimated US$50-US$60 billion dollars in subsidies on key staples such as petroleum products and utilities. The government used the savings to provide universal direct monthly cash transfers to each household (Khajehpour, 2013), direct assistance to enterprises adjusting to the new price structure, and direct assistance to the government agencies to help pay for higher energy bills.

The third subsidy reform event took place on April 24, 2014, when the Iranian government implemented the second phase of the Iranian subsidy reform plan, decreasing subsidies further and causing energy prices to experience another significant increase. Transportation fuel prices were increased by a higher percentage than natural gas prices were.

The fourth subsidy reform event took place on May 27, 2015, when the Iranian government further increased transportation fuel prices (but did not further increase natural gas prices), and abandoned the gasoline consumption quota restriction and the fuel card program altogether (Kheiravar, 2019).

Table 1 lists the four major Iranian subsidy reform events. Table A-1 in Appendix A summarizes the energy and utility prices during the subsidy reform.

As seen in Figure A-2 in Appendix A, despite the Iranian subsidy reform, gasoline prices in Iran continue to be among the lowest in the world in 2017. As seen in Figure A-3 in Appendix A, annual gasoline consumption in Iran ceased its long-term upward trend following the first three subsidy reform events, when the gasoline consumption quota was in place; but resumed its upward trend following the fourth subsidy reform event, when the gasoline consumption quota was removed. In contrast, as seen in Figure A-4 in Appendix A, annual diesel consumption in Iran continued its long-term upward trend following Events 1 and 2, but declined following Events 3 and 4.

[1] Each Iranian Toman is equivalent to 10 Iranian Rial (IRR).

4 Data

For our air quality data, we use data from the Tehran Air Quality Control Company[2] on the daily average concentrations and hourly mean concentrations of five air pollutants (CO, O_3, NO_2, PM_{10}, and SO_2) from 24 monitoring stations in Tehran over the period March 21, 2007 to March 19, 2017 (corresponding to the dates 1386/1/1 to 1395/29/12 in the Iranian Calendar). Figure A-5 in Appendix A maps the 24 local air quality monitoring stations in Tehran.

Since motor vehicle emissions are major sources of CO, O_3, NO_2, and PM_{10} in Tehran (Zerbonia and Soraya, 1978; Azarmi and Arhami, 2017; Heger and Sarraf, 2018), we analyze the effects of the Iranian subsidy reform on CO, O_3, NO_2, and PM_{10}. From the hourly mean air quality data, we create variables for the daily maximum pollution concentration for each of these four air pollutants (CO, O_3, NO_2, and PM_{10}). For each pollutant, each day, and each monitoring station, the daily maximum pollution concentration is the maximum value of all hourly values of that pollutant for that day and monitoring station. For each pollutant, there is a separate observation of the daily maximum pollution level for that pollutant for each day for each monitoring station. Table 2 presents summary statistics for the daily average pollution concentration and the daily maximum pollution concentration for each of the four air pollutants (CO, O_3, NO_2, and PM_{10}); as well as the daily average pollution concentration of SO_2, which we use to control for any changes in industrial activity that may have been correlated with the energy subsidy reform events.

Figure A-6 in Appendix A plots mean daily pollution levels for each of the four pollutants. Mean daily pollution levels are constructed by averaging the hourly mean concentration over all hours in a day and over all monitoring stations. The vertical lines indicate the dates of each of the four subsidy reform events: June 27, 2007; December 18, 2010; April 24, 2014; and May 27, 2015.

We use daily weather data from the National Oceanic and Atmospheric Administration (NOAA) (2018) for two weather stations near Tehran: the Mehrabad Airport weather monitoring station and the IKI Airport weather monitoring station. Table 3 presents summary statistics for the weather data, averaged over both weather stations near Tehran.

Figures 1 and 2 plot residuals from a regression of log daily average pollution concentration levels and log daily maximum pollution concentrations levels, respectively, on weather and seasonality covariates, year effects, and station fixed effects for each of the four air pol-

[2] http://air.tehran.ir/

lutants (CO, O_3, NO_2, and PM_{10}). The fitted lines are the predicted values of a regression of these residuals on subsidy reform dummies and a ninth-order polynomial time trend. The vertical lines indicate the dates of each of the four subsidy reform events. According to Figures 1 and 2, Events 1 and 2 seem to have led to a drop in daily average and daily maximum pollution concentrations of all four air pollutants. Each of the four subsidy reform events appear to have led to a decline in daily average and daily maximum pollution concentrations of O_3 and NO_2. The effects of Events 3 and 4 on daily average and daily maximum concentrations of CO and PM_{10} appear more mixed, however.

5 Methods

5.1 Conceptual Framework

We first begin with a conceptual framework that explains how a subsidy reform event may affect air pollution, and why the effects of fuel subsidies and subsidy reform on air quality are in part an empirical question.

There are several factors that affect how a fuel subsidy reform event may affect air pollution. First, the effect of a subsidy reform event on air pollution depends on the effects of the subsidy reform on fuel demand. How the subsidy reform event affects fuel demand depends in part on the price elasticity of demand. In their study of the effects of the Iranian subsidy reform on gasoline demand, Ghoddusi et al. (2022) find a consistent decline in the gasoline price elasticity following each of the first three subsidy reform events. It is possible that the gasoline subsidy elasticity may differ from the gasoline tax elasticity. In the previous literature, Li et al. (2014) find that, owing to perceived persistence and salience of taxes, consumers may respond more to taxes than to equal-sized changes in tax-inclusive gasoline prices;[3] it is possible that consumers may likewise respond differently to changes in subsidies than they would to equal-sized changes in prices. Moreover, since the second subsidy reform event coupled increases in energy prices with universal direct monthly cash transfers to each household (Khajehpour, 2013; Kheiravar, 2019), the effects of the second and subsequent subsidy reforms events may also depend in part on the income elasticity of fuel demand.

A second factor that affects how a subsidy reform event may affect air pollution is the location where the eventual consumption and use (burning) of the fuel takes place after it has been purchased. Iran's high fuel subsidies have led to lucrative opportunities for smuggling

[3]Brown et al. (2020) find that firms similarly respond more to an increase in tax per unit of production than they do to an equivalent price decrease.

fuel into neighboring markets and other countries (Ghoddusi et al., 2018; Khajehpour, 2018); the eventual use and combustion of the smuggled fuel would likely affect the local air quality of the country into which the fuel was smuggled more than it would affect the air quality in Iran. Similarly, subsidy reform events that include a monthly gasoline consumption quota (i.e., the first three subsidy reform events) may also create a domestic black market for heavily subsidized fuels, especially gasoline (Khajehpour, 2018), so that the eventual consumer of the fuel may not necessarily be the fuel card owner who purchased the fuel, and the location of the eventual fuel consumption may not necessarily be near where the original fuel card owner lives or works. Whether changes in fuel demand as a result of subsidy reform translate to changes in Iran's air quality may therefore depend in part on the price elasticities of smuggling versus domestic consumption. Ghoddusi et al. (2018) estimate the price elasticity of gasoline smuggling in Iran, and find that the foreign-to-home gasoline price ratios have a significant effect on the elasticity of demand. Likewise, whether the subsidy reform affects local air quality in Tehran may depend on how the subsidy reform affects fuel consumption and driving behavior in Tehran versus other parts of Iran. It is possible, for example, that the subsidy reform may affect where households decide to live, work, and drive. The possibility that transportation policies may affect the location and spatial distribution of driving has been previously examined in the context of driving regulations (Wolff, 2014; Gibson and Carnovale, 2015).

A third factor that affects how a subsidy reform event may affect air pollution is how the subsidy reform event affects transportation decisions more generally. Since the fuel card program that was implemented in the first subsidy reform event and that remained in place during the first three subsidy reform events was a monthly gasoline consumption quota for each vehicle, it is possible that the first three subsidy reform events may increase a household's incentives to purchase a second vehicle. The subsidy reform events may likewise affect individuals' incentives to take another mode of transportation, such as public transit or a taxi. The possibility that households may respond to transportation policies by purchasing a second vehicle and/or taking alternative modes of transportation has been previously examined in the context of driving restrictions (Davis, 2008; Gallego et al., 2013a; Zhang et al., 2017). Whether or not households decide to purchase a second vehicle or take alternative modes of transportation may affect how the subsidy reform affects fuel demand and how the subsidy reform affects the location of fuel consumption and use (combustion).

A fourth factor that affects how a subsidy reform event may affect air pollution is the timing of when the eventual consumption and use (burning) of the fuel takes place after it has been purchased. Since each of the four subsidy reform events involve fuel price increases, then if households anticipate the fuel price increases, it is possible that some households may purchase more fuel in advance of the next subsidy reform event. Coglianese et al. (2017) find evidence that forward-looking gasoline buyers in the United States take future tax changes into account when deciding how much gasoline to buy, thereby shifting gasoline purchases in anticipation of gasoline tax changes; it is possible that Iranian consumers may similarly shift gasoline purchases in advance of each subsidy reform event. Similarly, since the fuel card program that was implemented in the first subsidy reform event and that remained in place during the first three subsidy reform events was a monthly gasoline consumption quota for each vehicle, it is possible that the monthly quota may incentivize households to completely exhaust their quota by the end of the month, purchasing more than they otherwise would have at the end of the month so that they could purchase less at the beginning of the next month. Likewise, for households who have already exhausted their quota for a particular month before the end of that month, the monthly quota may incentivize households to purchase less fuel towards the end of that month since they have already exhausted their quota for that month, and to instead wait until the beginning of the next month to purchase more fuel. If these distortions in the timing of fuel purchases are merely changes in purchasing, storage, and stockpiling behavior and do not result in changes in the timing or location of driving, fuel consumption, and fuel combustion, however, then these fuel purchase timing distortions that result from anticipating or adjusting to the subsidy reform may not necessarily affect how the subsidy reform affects air pollution. It is possible, for example, that driving, commuting, and fuel consumption and use (combustion) decisions may be less elastic than fuel purchasing decisions are. As explained in more detail below, to examine the robustness of our results to any possible anticipation of or adjustment to each subsidy reform event, and to allow for possible differences in the short run and longer run responses, we run our regression discontinuity analysis using windows ranging from 8 to 30 weeks before and after each respective event.

A fifth factor that affects how a subsidy reform event may affect air pollution is how changes in fuel consumption and use (burning) affect air quality, which in turn depends on the sources and atmospheric chemistry of different air pollutants (Zhang et al., 2017). In Tehran, motor vehicle emissions are major sources of CO, O_3, NO_2, and PM_{10} (Zerbonia and Soraya, 1978; Azarmi and Arhami, 2017; Heger and Sarraf, 2018), but not a primary source of SO_2 (Massoudi, 1977; Zhang et al., 2017). The possible effects of changes in gasoline consumption and driving on ozone (O_3) are complicated (Zhang et al., 2017). A secondary pollutant, ozone (O_3) is not emitted directly but is formed in ambient air in the presence of sunlight by chemical reactions involving nitrogen oxides (NO_x), which consist of nitrogen oxide (NO) and nitrogen dioxide (NO_2); and volatile organic compounds (VOCs) (Lin, 2000; Lin et al., 2000, 2001; Lin, 2010). The rate of ozone production shows a nonlinear and non-monotonic dependence on precursor concentrations. Higher emissions of NO_x do not always result in higher levels of ozone pollution; in some cases, higher NO_x emissions may actually decrease ozone, a phenomenon known as NO_x titration (Lin, 2010). Owing to the non-monotonic relationship between emissions and ozone production, a subsidy reform event that decreases driving may not necessarily decrease ozone (O_3) (Zhang et al., 2017).

A sixth factor that affects how a subsidy reform event may affect air pollution is how changes in consumption of different fuels affect air pollution. Vehicles fueled by gasoline have different effects on air pollution than do vehicles fueled by diesel, and these effects vary by air pollutant. In the absence of particle traps, diesel CO emissions are similar to those from gasoline. Nevertheless, 'modern' diesel vehicles with particle traps have lower CO emissions and lower hydrocarbon emissions than gasoline vehicles (Jacobson et al., 2004). Diesel vehicles with or without a particle trap and without a NO_x control device emit 4 to 30 times more NO_x than do gasoline vehicles (Jacobson et al., 2004). In addition, diesel vehicles have higher particulate matter emission rates than gasoline vehicles (Onursal and Gautam, 1997; Zhang et al., 2017). Diesel vehicles with or without a particle trap and without a NO_x control device also emit a higher ratio of NO_2 to NO than do gasoline vehicles, and as a consequence, may increase O_3 particularly under certain circumstances (Jacobson et al., 2004; Zhang et al., 2017).

A seventh factor that affects how a subsidy reform event may affect air pollution is how the subsidy reform may effect energy consumption and emissions in non-transportation sectors. Energy subsidy reforms may include reforms not only to subsidies for transportation fuels but also to subsidies for residential and/or industrial sector energy as well, and the resulting changes in emissions in these other sectors may also impact air pollution. For example, since the third subsidy reform event increased transportation fuel prices by a higher percentage than it increased natural gas prices, and since the fourth subsidy increased transportation fuel prices but did not further increase natural gas prices, the effects of the third and fourth subsidy reform events may depend in part on natural gas consumption and its resulting emissions.

Thus, since there are many factors that affect how a subsidy reform event may affect air pollution, the effects of fuel subsidies and subsidy reform on air quality are in part an empirical question.

5.2 Regression Discontinuity Design

To analyze the impact of the energy subsidy reform on air quality, we use a regression discontinuity design. A regression discontinuity design can be used when observations can be ordered according to a forcing (or running) variable and the treatment is assigned above a given threshold.[4] In our case, the forcing variable is time and the threshold is the date a phase of the Iranian subsidy reform plan was implemented (Percoco, 2014). Previous studies that have used a regression discontinuity design with time as the forcing variable include Davis (2008), Davis and Kahn (2010), Auffhammer and Kellogg (2011), Chen and Whalley (2012), Bento et al. (2014), Burger et al. (2014), Grainger and Costello (2014), Anderson (2014), Salvo and Wang (2017), Zhang et al. (2017), Fuje (2019), and Si et al. (2022). Hausman and Rapson (2018) provide an excellent review of these studies and a guide for practitioners. In a regression discontinuity design, there is no value of the forcing variable at which we observe both treatment and control observations; instead, we extrapolate across covariate values, at least in a neighborhood of the discontinuity (Angrist and Pischke, 2009; Imbens and Lemieux, 2008).

Local polynomial methods are preferable to high-order global polynomial methods in regression discontinuity design because they avoid several of the methodological problems created by the use of global polynomials, such as erratic behavior near boundary points, counterintuitive weighting, overfitting, and general lack of robustness (Gelman and Imbens, 2019; Cattaneo and Titiunik, 2022). The order of the polynomial should always be low, to avoid overfitting and erratic behavior near the cutoff point. The default recommendation is local linear regression (Cattaneo and Titiunik, 2022).[5]

We use the local polynomial regression discontinuity robust bias-corrected confidence intervals and inference procedures developed in Calonico et al. (2014), Calonico et al. (2018), and Calonico et al. (2019). The confidence intervals are constructed using a bias-corrected regression discontinuity estimator together with a novel standard error estimator proposed

[4]Cattaneo and Titiunik (2022) provide a recent curated review of the methodological literature on the analysis and interpretation of regression discontinuity designs.

[5]Pei et al. (2021) provides a data-driven choice of the order of the local polynomial in regression discontinuity designs, based on minimizing the asymptotic mean squared error (MSE) of the regression discontinuity point estimator. Since we run multiple regression discontinuity regressions for the different pollutants and subsidy reform events, we opt to use the default recommendation of a local linear regression rather than use a data-driven approach to choose a potentially different local polynomial order for each of our many regression discontinuity regressions.

in Calonico et al. (2014). In particular, the confidence intervals are constructed using an alternative asymptotic theory for bias-corrected local polynomial estimators in the context of regression discontinuity designs, which leads to a different asymptotic variance in general and thus justifies a new standard error estimator. Bandwidth choices that minimize asymptotic mean squared error (MSE) are derived following Imbens and Kalyanaraman (2012). Calonico et al. (2014) find that the resulting data-driven confidence intervals performed very well in simulations, suggesting in particular that they provide a robust (to the choice of bandwidths) alternative when compared to the conventional confidence intervals routinely employed in empirical work. Hyytinen et al. (2018) similarly find that bias-corrected regression discontinuity design estimates that apply robust inference are in line with the experimental estimate from an experiment that takes place exactly at the cutoff.

In particular, we run the local linear regression discontinuity regressions with robust confidence intervals proposed in Calonico et al. (2014) of residuals from a regression of log daily average pollution concentration levels on weather and seasonality covariates, station fixed effects, and year effects for each of the four air pollutants (CO, O_3, NO_2, and PM_{10}). We similarly run the local linear regression discontinuity regressions with robust confidence intervals proposed in Calonico et al. (2014) of residuals from a regression of log daily maximum pollution concentration levels on weather and seasonality covariates and station fixed effects for each of the four air pollutants (CO, O_3, NO_2, and PM_{10}). The weather covariates are a fourth-order polynomial in log daily average temperature and log daily max sustained wind speed. The seasonality covariates include dummies for each month of the year and dummies for each day of the week.

Formally, for each of the four air pollutants j, our first-stage regression is given by:

$$y_{ijt} = x_t'\gamma + \tau_t + \alpha_i + \epsilon_{ijt}, \tag{1}$$

where the dependent variable y_{ijt} is either the log daily average or the log daily maximum pollution concentration of pollutant j measured at station i on day t; x_t is a vector of weather and seasonality covariates; τ_t are year effects; and α_i is a station fixed effect. The four air pollutants j are CO, O_3, NO_2, and PM_{10}. The vector of weather and seasonality covariates x_t includes indicator variables for month of the year and day of the week; and fourth-order polynomials in log daily average temperature and log daily maximum sustained wind speed.

In the second stage, for each of the four subsidy reform events in Table 1 and for each of the four air pollutants (CO, O_3, NO_2,and PM_{10}), we take the residuals $\hat{\epsilon}_{ijt}$ from the first-stage regression in equation (1) and run local linear regression discontinuity regressions of these residuals $\hat{\epsilon}_{ijt}$ to analyze the effects of that subsidy reform event event on that air pollutant, using the method for local linear regression discontinuity regressions with robust confidence intervals proposed in Calonico et al. (2014).

Our regression discontinuity design addresses the potential bias caused by time-varying omitted variables. Within a narrow time window, the unobserved factors influencing air quality are likely to be similar so that observations when the subsidy reform was not in effect provide a comparison group for observations when the subsidy reform was in effect. The station fixed effects α_i control for time-invariant station heterogeneity. The indicator variables for month of the year control for monthly variation in driving patterns and other factors that affect air quality. Similarly, the indicator variables for day of the week control for intra-week variation in driving patterns and other factors that affect air quality.[6] Our regression discontinuity design includes covariates that enter in an additively separable, linear-in-parameters way; Calonico et al. (2019) shows that the resulting covariate-adjusted regression discontinuity estimator remains consistent for the standard regression discontinuity treatment effect and can achieve substantial efficiency gains relative to the unadjusted regression discontinuity estimator.

Following Gallego et al. (2013b) and Zhang et al. (2017), in order to control for any changes in industrial activity that may have been correlated with the energy subsidy reform events, we run specifications that include sulfur dioxide (SO_2) as a control variable in the first-stage regression. In Tehran, motor vehicle emissions are major sources of CO, O_3, NO_2, and PM_{10} (Zerbonia and Soraya, 1978; Azarmi and Arhami, 2017; Heger and Sarraf, 2018), but not a primary source of sulfur dioxide (SO_2) (Massoudi, 1977; Zhang et al., 2017). Instead, industrial sources, domestic and commercial heating are responsible for nearly all the SO_2 emissions in Tehran (Massoudi, 1977). Thus, since SO_2 may be more related to industrial activity than to driving behavior (Zhang et al., 2017), we run additional specifications that include sulfur dioxide (SO_2) as a control variable in the first-stage regression in order to control for any changes in industrial activity that may have been correlated with the energy subsidy reform events.

In particular, for each of the four air pollutants j, our first-stage regression that controls for SO_2 is given by:

$$y_{ijt} = \beta so2_{it} + x_t'\gamma + \tau_t + \alpha_i + \epsilon_{ijt}, \tag{2}$$

where the dependent variable y_{ijt} is either the log daily average or the log daily maximum

[6] For the year effects τ_t, we define each year to be from July 1st to June 30th so that Event 2, which is the subsidy reform event with the largest changes in prices, occurs roughly in the middle of the year.

pollution concentration of pollutant j measured at station i on day t; $so2_{it}$ is log daily average SO_2; x_t is a vector of weather and seasonality covariates; τ_t are year effects; and α_i is a station fixed effect. The vector of weather and seasonality covariates x_t includes indicator variables for month of the year and day of the week; and fourth-order polynomials in log daily average temperature and log daily maximum sustained wind speed.

In the second stage, for each of the four subsidy reform events in Table 1, we take the residuals $\hat{\epsilon}_{ijt}$ from the first-stage regression that controls for SO_2 in equation (2), and run local linear regression discontinuity regressions of these residuals $\hat{\epsilon}_{ijt}$ for each of the four air pollutants (CO, O_3, NO_2, and PM_{10}) to analyze the effects of that subsidy reform event event on that air pollutant, using the method for local linear regression discontinuity regressions with robust confidence intervals proposed in Calonico et al. (2014).

To examine the robustness of our results to any possible anticipation of or adjustment to each subsidy reform event, and to allow for possible differences in the short run and longer run responses, we run the second-stage local linear regression discontinuity regressions with robust confidence intervals using windows ranging from 8 to 30 weeks before and after each respective event.[7]

6 Results

6.1 Local Linear Regression Discontinuity Results

The results of the local linear regression discontinuity regressions with robust confidence intervals of the residuals $\hat{\epsilon}_{ijt}$ from the first-stage regression in equation (1) for windows ranging from 8 to 30 weeks before and after each respective event for each of the four air pollutants (CO, O_3, NO_2, and PM_{10}) are presented in Tables A-2.a-A-2.d in Appendix A.

In order to control for any changes in industrial activity that may have been correlated with the energy subsidy reform events, we run additional specifications that include sulfur dioxide (SO_2) as a control variable in the first-stage regression. In Tehran, industrial sources, domestic and commercial heating are responsible for nearly all the SO_2 emissions (Massoudi, 1977). The results of the local linear regression discontinuity regressions with robust confidence intervals of the residuals $\hat{\epsilon}_{ijt}$ from the first-stage regression that controls for SO_2 in equation (2) for each of the four air pollutants (CO, O_3, NO_2, and PM_{10}) for

[7]We also run a set of regressions allowing for adjustment over time, adapting a model developed by Gallego et al. (2013b). As these adjustment models do not pass the placebo tests, however, this evidence is weak at best and we therefore do not present these results.

windows ranging from 8 to 30 weeks before and after each respective event are presented in Tables 4.a-4.d.

We also run a set of local linear regression discontinuity regressions with robust confidence intervals in which we bootstrap the standard errors over both stages of the estimation, where the first stage is the first-stage regression in equation (1) of log daily average pollution concentration levels on weather and seasonality covariates, station fixed effects, and year effects from which we derive residuals $\hat{\epsilon}_{ijt}$; and the second stage is the local linear regression of residuals $\hat{\epsilon}_{ijt}$. In particular, monitoring stations are randomly drawn from the data set with replacement to generate multiple independent panels each with the sample number of stations in the original data set. We then run both stages on each of the new panels. The standard errors are then formed by taking the standard deviation of the bias-corrected local-polynomial regression discontinuity estimates from each of the panels. Only CO and O_3 had enough observations to run this bootstrap, and only for windows ranging from 10 to 30 weeks before and after each respective event. The results are presented in Tables 5.a-5.d.

We also run a set of local linear regression discontinuity regressions with robust confidence intervals in which we bootstrap the standard errors over both stages of the estimation, where the first stage is the first-stage regression that controls for SO_2 in equation (2). Only CO had enough observations to run this bootstrap, and only for the window from 30 weeks before to 30 weeks after each respective event. The results are presented in Table 6.

Across the different specifications in Tables 4.a-6 and Appendix A Tables A-2.a-A-2.d, we find the following robust results. Event 1 had a robust significant negative effect on daily maximum O_3, causing daily maximum O_3 to decrease by 60.43 to 89.35 percentage points. As seen in the summary statistics for daily maximum O_3 in Table 2, the standard deviation of the daily maximum O_3 concentration is over 50 percent of its mean; and the maximum value of the daily maximum O_3 concentration is 191.33 times its minimum value, nearly 4 times its mean, and over 2.7 times the U.S. federal national ambient air quality standard (NAAQS) for O_3 of 70 parts per billion (ppb) for the fourth-highest daily maximum 8-hour O_3 concentration (U.S. Environmental Protection Agency (EPA), 2020b). Thus, decreases in daily maximum O_3 concentrations of 60.43 to 89.35 percentage points as a result of the first subsidy reform event are reasonable, since the high values of daily maximum O_3 concentrations were extremely high. In addition to its robust significant negative effect on daily maximum O_3, Event 1 also had a significant negative effect on daily average O_3 that was somewhat robust as well, causing daily average O_3 to decrease by 39.42 to 52.65 percentage points. The smaller effect on daily average O_3 concentrations seems reasonable, and consistent with Event 1 reducing the extremely high daily maximum O_3 concentrations.

Event 1 also had a robust significant negative effect on daily maximum PM_{10}, causing daily maximum PM_{10} to decrease by 55.50 to 78.77 percentage points. As seen in the summary statistics for daily maximum PM_{10} in Table 2, the standard deviation of the daily maximum PM_{10} concentration is nearly 60 percent of its mean; and the maximum value of the daily maximum PM_{10} concentration is nearly 25 times its mean, and over 14 times the U.S. federal national ambient air quality standard (NAAQS) for PM_{10} of 150 $\mu g/m^3$ (U.S. Environmental Protection Agency (EPA), 2020a). Thus, decreases in daily maximum PM_{10} concentrations of 55.50 to 78.77 percentage points as a result of the first subsidy reform event are reasonable, since the high values of daily maximum PM_{10} concentrations were extremely high. Event 1 also had a significant negative effect on daily average PM_{10} that was fairly robust as well, causing daily average PM_{10} to decrease by 43.96 to 57.14 percentage points. The somewhat smaller effect on daily average PM_{10} concentrations seems reasonable, and consistent with Event 1 reducing the extremely high daily maximum PM_{10} concentrations.

Event 2 had a fairly robust significant negative effect on CO, causing daily maximum CO to decrease by 22.58 to 42.70 percentage points, and daily average CO to decrease by 19.90 to 42.01 percentage points. Event 2 had a fairly robust significant negative effect on O_3, causing daily maximum O_3 to decrease by 32.07 to 52.44 percentage points, and daily average O_3 to decrease by 27.76 to 50.50 percentage points. Event 2 had a fairly robust significant negative effect on daily maximum NO_2, causing daily maximum NO_2 to decrease by 10.79 to 24.88 percentage points.

Event 3 did not appear to have any significant effect on any pollutant that was robust across multiple specifications.

Event 4 had a robust significant negative effect on O_3, causing daily maximum O_3 to decrease by 22.26 to 37.14 percentage points, and daily average O_3 to decrease by 19.05 to 33.81 percentage points. Event 4 also had a robust significant positive effect on daily average PM_{10}, causing daily average PM_{10} to increase by 14.88 to 55.23 percentage points.

6.2 Model Validity

An underlying assumption for regression discontinuity designs is that the forcing variable, which in our case is time, should be balanced around the cutoff, which in the case of our regression discontinuity model of the effect of a particular subsidy reform event is the date of implementation of that subsidy reform event (Imbens and Lemieux, 2008; Lee and Lemieux, 2010; Beach and Jones, 2017). For each of the four subsidy reform events, to examine the distribution of the forcing variable (time) at the threshold (the date of that subsidy reform event), we plot the number of observations per week against the week away from the date of that subsidy reform event for each pollutant. The results for each pollutant for each of the four subsidy reform events are in Figures A-7-A-10 in Appendix A. As these graphs show, for each of the four subsidy reform events, the distribution is continuous around the threshold, so the forcing variable is balanced around the cutoff. This continuity of the distribution around the threshold is evidence against any manipulation of whether air quality measurements were taken before or after each of the four subsidy reform events.

Another underlying assumption for regression discontinuity designs is that there are no discontinuous changes in the control variables at the time of the various subsidy reform events. To examine if there were any discontinuous changes in the control variables at the time of the various subsidy reform events, Tables A-3 and A-4 in Appendix A present results of regression discontinuity analyses of our daily weather variables: log daily average temperature and log daily maximum sustained wind speed, respectively. Results confirm that there are no discontinuous changes in any of the weather variables at the time of any of the subsidy reform events.

6.3 Placebo Tests

To examine the robustness of our results, we run placebo tests for each of our regression discontinuity regression models using placebo subsidy reform dates instead of the actual subsidy reform dates as the treatment in Appendix B. If we do not find significant treatment effects where there has been no treatment, then this means that our results are robust to our tests. As presented in more detail in Appendix B, results of the placebo tests show that none of the placebo treatment effects are significant and negative for any of the pollutants, and that the few placebo treatment effects that are statistically significant at a 5% level are positive, not negative. Thus, since we do not find any significant negative treatment effects where there has been no treatment, and since we find very few significant treatment effects where there has been no treatment, this means that our results are robust to our tests.

7 Discussion and Conclusion

Our results provide evidence across multiple different empirical specifications that the subsidy reform in Iran, particularly subsidy reforms that both increased energy prices and restricted gasoline consumption, led to improvements in air quality. In particular, the first subsidy reform event, which increased gasoline prices and implemented a gasoline consumption quota, led to a dramatic decline in concentrations of O_3 and PM_{10}. The second subsidy reform event, which further increased energy prices and decreased energy subsidies, led to declines in concentrations of CO, O_3, and NO_2. In contrast, the third subsidy reform event (which increased transportation fuel prices by a larger percentage than it increased natural gas prices) and the fourth subsidy reform event (which increased transportation fuel prices but not natural gas prices, and which removed the gasoline consumption quota) were less effective in reducing air pollution. The third subsidy reform event, which increased transportation fuel prices by a larger percentage than it increased natural gas prices, did not appear to have any significant effect on any pollutant that was robust across multiple specifications. The fourth subsidy reform event, which increased transportation fuel prices but not natural gas prices, and which removed the gasoline consumption quota, had mixed results: while it led to declines in O_3 concentrations, it also led to increases in daily average PM_{10}.

The possible effects of changes in gasoline consumption and driving on ozone (O_3) are more complicated (Zhang et al., 2017). Higher emissions of NO_x do not always result in higher levels of ozone pollution; in some cases, higher NO_x emissions may actually decrease ozone (Lin, 2010). Nevertheless, we find evidence that subsidy reform can decrease O_3, as Events 1, 2, and 4 each led to declines in O_3 concentrations.

Vehicles fueled by gasoline have different effects on air pollution than do vehicles fueled by diesel, and these effects vary by air pollutant. In the absence of particle traps, diesel CO emissions are similar to those from gasoline (Jacobson et al., 2004; Onursal and Gautam, 1997; Zhang et al., 2017). As seen in Figure A-3 in Appendix A, gasoline consumption ceased its long-term upward trend following the first three subsidy reform events, when the gasoline consumption quota was in place; but resumed its upward trend following the fourth subsidy reform event, when the gasoline consumption quota was removed. In contrast, as seen in Figure A-4 in Appendix A, diesel consumption continued its long-term upward trend following Events 1 and 2, but declined following Events 3 and 4. In conjunction with our results that the first two subsidy reform events led to improvements in air quality and declines in concentrations of O_3, PM_{10}, CO, and NO_2, these trends in gasoline and diesel consumption possibly suggest that attenuating the upward trend in gasoline consumption may matter more for reducing air pollution in Tehran than does attenuating the upward trend in diesel consumption.

There are several possible explanations for why the first subsidy reform event (which increased gasoline prices and implemented a gasoline consumption quota) and the second subsidy reform (which increased energy prices and decreased energy subsidies) both led to improvements in air quality; while the third subsidy reform event (which increased transportation fuel prices by a larger percentage than it increased natural gas prices) and the fourth subsidy reform event (which increased transportation fuel prices but not natural gas prices, and which removed the gasoline consumption quota) were less effective in reducing air pollution.

One possible reason why the later subsidy reform events may have been less effective in reducing air pollution is that consumers may have become less willing or able to continue to further reduce fuel consumption over the long term and for each subsequent subsidy reform event. Ghoddusi et al. (2022) find that consumers were becoming less responsive to increases in fuel prices at each subsequent subsidy reform event. If consumers were becoming less willing or able to continue to further reduce fuel consumption for each subsequent subsidy reform event, then this would mean that energy consumption, and hence air pollution, would not decline as much in the later subsidy reform events.

A second possible reason why the later subsidy reform events may have been less effective in reducing air pollution is that, if domestic fuel consumption is less elastic than fuel smuggling is at higher fuel prices, then it is possible that the later subsidy reform events, which further increased fuel prices, may potentially have reduced fuel smuggling to other countries more than it did domestic fuel consumption. As a consequence, domestic fuel consumption, and hence local air pollution, would not decline as much in the later subsidy reform events.

Third, Event 4 may have been less effective in reducing air pollution because it removed the gasoline consumption quota that was implemented by the first subsidy reform event and that had remained in place during the first three subsidy reform events. As seen in Figure A-3 in Appendix A, gasoline consumption ceased its long-term upward trend following the first three subsidy reform events, when the gasoline consumption quota was in place; but resumed its upward trend following the fourth subsidy reform event, when the gasoline consumption quota was removed. Since gasoline consumption resumed its upward trend following the removal of the gasoline consumption quota during Event 4, air pollution may have increased as a result of Event 4 as well. For example, increases in gasoline consumption may have contributed to the increases in PM_{10} that occurred following Event 4.

A fourth possible reason why the later subsidy reform events may have been less effective in reducing air pollution is that Event 3 did not increase natural gas prices by as much as it did transportation fuel prices, and Event 4 did not include increase natural gas prices at all. Smaller increases in natural gas prices would result in smaller decreases in natural gas consumption in the industrial and residential sectors. Our use of SO_2 as a control variable enables us to control for any changes in industrial activity that may have been correlated with the energy subsidy reform events, and therefore at least partially controls for the former, but may not fully control for the latter. Smaller decreases in natural gas consumption in the residential sector as a result of Events 3 and 4 may therefore potentially explain at least in part why these subsidy reform events were less effective in reducing air pollution.

Our results therefore provide evidence across multiple different empirical specifications that the subsidy reform in Iran, particularly subsidy reforms that both increased energy prices and restricted gasoline consumption, led to improvements in air quality. In contrast, subsidy reforms that increased transportation fuel prices but did not also restrict gasoline consumption were less effective in reducing air pollution. One possible reason why a quantity instrument (the gasoline consumption quota) may have been needed in addition to a price instrument (the increases in energy prices) is that the magnitude of the price instrument was insufficient: although each of the subsidy reform events increased fuel prices, fossil fuels were still heavily subsidized. As seen in Figure A-2 in Appendix A, despite the Iranian subsidy reform, gasoline prices in Iran continue to be among the lowest in the world in 2017. In addition, in order to reduce air pollution, it may be important to increase energy prices not only for transportation fuels but also for natural gas as well.

As there are many channels through which the fuel subsidy reform events may affect air quality, an advantage of our empirical approach is that it does not make any assumptions about the particular channel(s) or mechanism(s) through which each subsidy reform event may affect air quality, but instead allows for any of a number of these many channels and estimates their net effect on each subsidy reform event. In future work, we hope to obtain sufficiently detailed data, including sufficiently detailed data on gasoline, diesel, and natural gas consumption; fuel smuggling; driving behavior; traffic flows; vehicle ownership; storage and stockpiling behavior; fuel card use behavior; and transportation mode choices to enable us to better understand and tease out the mechanisms that led the later subsidy reform events to be less effective than the earlier subsidy reform events in reducing air pollution.

In addition, in future work we hope to analyze the health impacts of the changes in air quality resulting from the subsidy reform. Furthermore, the Iranian government recently announced in November 2018 that it would reintroduce the fuel cards that it had previously abandoned in the fourth subsidy reform event in 2015 (Khajehpour, 2018); in future work we hope to also analyze the effects of the recent reintroduction of the fuel cards, and to obtain the detailed data needed to do so.

Gasoline taxes have been touted by many economists as an efficient and relatively simple tool to address environmental concerns and other problems associated with gasoline consumption. Nevertheless, rather than removing subsidies and increasing gasoline taxes, many countries still subsidize gasoline, which may have the opposite effect of exacerbating air pollution and other problems associated with gasoline consumption. Our research provides suggestive evidence that energy subsidy reform can have the beneficial effect of reducing air pollution, particularly when the reduction in subsidies is coupled with measures to promote energy conservation, and when subsidies on all forms of energy are removed.

References

Abdallah Mostafa, M. G. (2021). The Impact of Energy Subsidy Reform on Economic Growth in Egypt Over the Period from 2013 to 2020. *International Journal of Energy Economics and Policy*, 11(4):31–42.

Adetutu, M. O. and Weyman-Jones, T. G. (2019). Fuel Subsidies Versus Market Power: Is There a Countervailing Second-Best Optimum? *Environmental and Resource Economics*, 74:1619–1646.

Aghaei, M. and Lin Lawell, C.-Y. C. (2022). Energy, Economic Growth, Inequality, and Poverty in Iran. *Singapore Economic Review*, 67(2):733–754.

Aldy, J. E. (2013). Eliminating Fossil Fuel Subsidies. In Greenstone, M., Harris, M., Li, K., Looney, A., and Patashnik, J., editors, *15 Ways to Rethink the Federal Budget*, pages 31–35. The Hamilton Project, Brookings Institution, Washington, DC.

Anderson, M. L. (2014). Subways, Strikes, and Slowdowns: The Impacts of Public Transit on Traffic Congestion. *American Economic Review*, 104(9):2763–2796.

Angrist, J. and Pischke, J.-S. (2009). *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton University Press.

Auffhammer, M. and Kellogg, R. (2011). Clearing the Air?: The Effects of Gasoline Content Regulation on Air Quality. *American Economic Review*, 101(6):2687–2722.

Aune, F. R., Grimsrud, K., Lindholt, L., Rosendahl, K. E., and Storrøsten, H. B. (2017). Oil Consumption Subsidy Removal in OPEC and Other Non-OECD Countries: Oil Market Impacts and Welfare Effects. *Energy Economics*, 68:395–409.

Azarmi, F. and Arhami, M. (2017). Air Pollution Challenges in the Megacity of Tehran, Iran. *em: The Magazine for Environmental Manager*, April 2017.

Balke, N. S., Plante, M., and Yücel, M. (2015). Fuel Subsidies, the Oil Market and the World Economy. *Energy Journal*, 36(SI1):99–127.

Beach, B. and Jones, D. (2017). Gridlock: Ethnic Diversity in Government and the Provision of Public Goods. *American Economic Journal: Economic Policy*, 9(1):112–136.

Beaudoin, J. and Lin Lawell, C.-Y. C. (2022). Is Public Transit's 'Green' Reputation Deserved?: Evaluating the Effects of Transit Supply on Air Quality. Working paper, Cornell University.

Bento, A., Kaffine, D., Roth, K., and Zaragoza-Watkins, M. (2014). The Effects of Regulation in the Presence of Multiple Unpriced Externalities: Evidence from the Transportation Sector. *American Economic Journal: Economic Policy*, 6(3):1–29.

Brown, J. P., Maniloff, P., and Manning, D. T. (2020). Spatially Variable Taxation and Resource Extraction: The Impact of State Oil Taxes on Drilling in the US. *Journal of Environmental Economics and Management*, 103:102354.

Burger, N. E., Kaffine, D. T., and Yu, B. (2014). Did California's Hand-Held Cell Phone Ban Reduce Accidents? *Transportation Research Part A: Policy and Practice*, 66:162–172.

BuShehri, M. A. and Wohlgenant, M. K. (2002). Measuring the Welfare Effects of Reducing a Subsidy on a Commodity Using Micro-Models: An Application to Kuwait's Residential Demand for Electricity. *Energy Economics*, 34(2):419–425.

Calonico, S., Cattaneo, M. D., and Farrell, M. H. (2018). On the Effect of Bias Estimation on Coverage Accuracy in Nonparametric Inference. *Journal of the American Statistical Association*, 113(522):767–779.

Calonico, S., Cattaneo, M. D., Farrell, M. H., and Titiunik, R. (2019). Regression Discontinuity Designs Using Covariates. *Review of Economics and Statistics*, 101(3):442–451.

Calonico, S., Cattaneo, M. D., and Titiunik, R. (2014). Robust Nonparametric Confidence Intervals for Regression-Discontinuity Designs. *Econometrica*, 82(6):2295–2326.

Cattaneo, M. D. and Titiunik, R. (2022). Regression discontinuity designs. *Annual Review of Economics*, 14(1):821–851.

Chen, Y. and Whalley, A. (2012). Green Infrastructure: The Effects of Urban Rail Transit on Air Quality. *American Economic Journal: Economic Policy*, 4(1):58–97.

Coady, D., Parry, I., Sears, L., and Shang, B. (2017). How Large Are Global Fossil Fuel Subsidies? *World Development*, 91:11–27.

Coglianese, J., Davis, L. W., Kilian, L., and Stock, J. H. (2017). Anticipation, Tax Avoidance, and the Price Elasticity of Gasoline Demand. *Journal of Applied Econometrics*, 32(1):1–15.

Davis, L. (2008). The Effect of Driving Restrictions on Air Quality in Mexico City. *Journal of Political Economy*, 116:38–81.

Davis, L. W. (2014). The Economic Cost of Global Fuel Subsidies. *American Economic Review*, 104(5):581–85.

Davis, L. W. (2017). The Environmental Cost of Global Fuel Subsidies. *Energy Journal*, 38(SI1):7–27.

Davis, L. W. and Kahn, M. E. (2010). International Trade in Used Vehicles: The Environmental Consequences of NAFTA. *American Economic Journal: Economic Policy*, 2(4):58–82.

Enriquez, S., Larsen, B., and Sánchez-Triana, E. (2018). Local Environmental Externalities due to Energy Price Subsidies: A Focus on Air Pollution and Health. Energy Subsidy Reform Assessment Framework (ESRAF) Good Practice Note 8, World Bank Group.

Farzanegan, M. R. and Krieger, T. (2018). Oil Rents Shocks and Inequality in Iran. CESifo Working Paper Series 6876, CESifo Group Munich.

Ferraresi, M., Kotsogiannis, C., and Rizzo, L. (2018). Decentralization and Fuel Subsidies. *Energy Economics*, 74:275–286.

Fuje, H. (2019). Fossil Fuel Subsidy Reforms, Spatial Market Integration, and Welfare: Evidence From a Natural Experiment in Ethiopia. *American Journal of Agricultural Economics*, 101(1):270–290.

Gallego, F., Montero, J.-P., and Salas, C. (2013a). The Effect of Transport Policies on Car Use: A Bundling Model With Applications. *Energy Economics*, 40:S85–S97.

Gallego, F., Montero, J.-P., and Salas, C. (2013b). The Effect of Transport Policies on Car Use: Evidence from Latin American Cities. *Journal of Public Economics*, 107:47–62.

Gelan, A. U. (2018). Kuwait's Energy Subsidy Reduction: Examining Economic and CO2 Emission Effects With or Without Compensation. *Energy Economics*, 71:186–200.

Gelman, A. and Imbens, G. (2019). Why High-Order Polynomials Should Not Be Used in Regression Discontinuity Designs. *Journal of Business & Economic Statistics*, 37(3):447–456.

Ghandi, A. and Lin, C.-Y. C. (2012). Do Iran's Buy-Back Service Contracts Lead to Optimal Production?: The Case of Soroosh and Nowrooz. *Energy Policy*, 42(C):181–190.

Ghandi, A. and Lin Lawell, C.-Y. C. (2017). On the Rate of Return and Risk Factors to International Oil Companies in Iran's Buy-Back Service Contracts. *Energy Policy*, 103:16–19.

Ghoddusi, H., Morovati, M., and Rafizadeh, N. (2022). Dynamics of Fuel Demand Elasticity: Evidence from Iranian Subsidy Reforms. *Energy Economics*, 110:106009.

Ghoddusi, H., Rafizadeh, N., and Rahmati, M. H. (2018). Price Elasticity of Gasoline Smuggling: A Semi-Structural Estimation Approach. *Energy Economics*, 71:171–185.

Ghosh, P. P. (2022). Impact of india's diesel subsidy reforms and pricing policy on growth and inflation. *Energy Economics*, 113:106195.

Gibson, M. and Carnovale, M. (2015). The effects of road pricing on driver behavior and air pollution. *Journal of Urban Economics*, 89:62–73.

Grainger, C. A. and Costello, C. J. (2014). Capitalizing Property Rights Insecurity in Natural Resource Assets. *Journal of Environmental Economics and Management*, 67(2):224–240.

Guillaume, D., Zytek, R., and Farzin, M. R. (2011). Iran: The Chronicles of the Subsidy Reform. IMP Working Paper No. WP/11/167, International Monetary Fund.

Gürer, N. and Ban, J. (2000). The Economic Cost of Low Domestic Product Prices in OPEC Member Countries. *OPEC Energy Review*, 22(2):143–183.

Hahn, R. W. and Metcalfe, R. D. (2021). Efficiency and equity impacts of energy subsidies. *American Economic Review*, 111(5):1658–88.

Haqiqi, I. and Manzoor, D. (2012). Environmental Impacts of Phasing Out Energy Subsidies. Working paper, Imam Sadiq University.

Hartley, P. and Medlock, K. B. (2008). A Model of the Operation and Development of a National Oil Company. *Energy Economics*, 30(5):2459–2485.

Hausman, C. and Rapson, D. S. (2018). Regression Discontinuity in Time: Considerations for Empirical Applications. *Annual Review of Resource Economics*, 10(1):533–552.

Heger, M. and Sarraf, M. (2018). Air Pollution in Tehran: Health Costs, Sources, and Policies. Environment and Natural Resources Global Practice Discussion Paper No. 6, World Bank.

Hosseini, V. and Shahbazi, H. (2016). Urban Air Pollution in Iran. *Iranian Studies*, 49(6):1029–1046.

Hyytinen, A., Meriläinen, J., Saarimaa, T., Toivanen, O., and Tukiainena, J. (2018). When Does Regression Discontinuity Design Work?: Evidence from Random Election Outcomes. *Quantitative Economics*, 9(2):1019–1051.

Imbens, G. and Kalyanaraman, K. (2012). Optimal Bandwidth Choice for the Regression Discontinuity Estimator. *The Review of Economic Studies*, 79(3):933–959.

Imbens, G. and Lemieux, T. (2008). Regression Discontinuity Designs: A Guide to Practice. *Journal of Econometrics*, 142(2):615–635.

Jacobson, M. Z., Seinfeld, J. H., Carmichael, G. R., and Streets, D. G. (2004). The Effect on Photochemical Smog of Converting the U.S. Fleet of Gasoline Vehicles to Modern Diesel Vehicles. *Geophysical Research Letters*, 31(2):L02116.

Khajehpour, B. (2013). What to Do About Iran's Subsidy Reforms? *Al-Monitor*, October 16, 2013.

Khajehpour, B. (2018). Iran Reintroduces Fuel Cards to Combat Smuggling. *Al-Monitor*, December 3, 2018 .

Kheiravar, K. H. (2019). Economic and Econometric Analyses of the World Petroleum Industry, Energy Subsidies, and Air Pollution. Ph.D. Dissertation, University of California at Davis.

Lee, D. and Lemieux, T. (2010). Regression Discontinuity Designs in Economics. *Journal of Economic Literature*, 48:281–355.

Li, S., Linn, J., and Muehlegger, E. (2014). Gasoline Taxes and Consumer Behavior. *American Economic Journal: Economic Policy*, 6(4):302–342.

Lin, C.-Y. C. (2000). Trends In Ozone Smog. Senior Thesis, Harvard University.

Lin, C.-Y. C. (2010). A Spatial Econometric Approach to Measuring Pollution Externalities: An Application to Ozone Smog. *Journal of Regional Analysis and Policy*, 40(1):1–19.

Lin, C.-Y. C., Jacob, D. J., and Fiore, A. M. (2001). Trends in Exceedances of the Ozone Air Quality Standard in the Continental United States, 1980–1998. *Atmospheric Environment*, 35(19):3217 – 3228.

Lin, C.-Y. C., Jacob, D. J., Munger, J. W., and Fiore, A. M. (2000). Increasing Background Ozone in Surface Air Over the United States. *Geophysical Research Letters*, 27(21):3465–3468.

Lin, C.-Y. C. and Prince, L. (2009). The Optimal Gas Tax for California. *Energy Policy*, 37(12):5173–5183.

Lin, C.-Y. C. and Zeng, J. J. (2014). The Optimal Gasoline Tax for China. *Theoretical Economics Letters*, 4(4):270–278.

Lin Lawell, C.-Y. C. (2017). Global Gasoline Prices: The Need to Raise Gasoline Taxes. *Nature Energy*, 2:Article 16206.

Massoudi, M. (1977). Air Pollution Source Inventory for Tehran — Methodology and Approach. *IFAC Proceedings Volumes*, 10(7):675–680.

National Oceanic and Atmospheric Administration (NOAA) (2018). Synoptic Weather Data for Weather Monitoring Station in Tehran. `www.noaa.gov`. Accessed: 1 February 2018.

Onursal, B. and Gautam, S. (1997). Vehicular Air Pollution: Experiences from Seven Latin American Urban Centers. World Bank Technical Paper No. 373, World Bank.

Parry, I., Heine, D., Lis, E., and Li, S. (2014). *Getting Energy Prices Right: From Principle to Practice*. International Monetary Fund Press, Washington, DC.

Pei, Z., Lee, D. S., Card, D., and Weber, A. (2021). Local polynomial order in regression discontinuity designs. *Journal of Business and Economic Statistics*, 40(3):1259–1267.

Percoco, M. (2014). *Regional Perspectives on Policy Evaluation*. Springer, Berlin.

Rezagholizadeh, M., Lin Lawell, C.-Y. C., and Yavari, K. (2022). An Analysis of the Conditional Relationship Between Risk and Return in the Tehran Stock Exchange. *Iranian Economic Review*, 26(1):79–107.

Ross, M. L., Hazlett, C., and Mahdavi, P. (2017). Global Progress and Backsliding on Gasoline Taxes and Subsidies. *Nature Energy*, 2:Article 16201.

Salehi-Isfahani, D. (1996). Government Subsidies and Demand for Petroleum Products in Iran. Oxford Institute for Energy Studies WPM 22.

Salvo, A. and Wang, Y. (2017). Ethanol-Blended Gasoline Policy and Ozone Pollution in Sao Paulo. *Journal of the Association of Environmental and Resource Economists*, 4(3):731–794.

Sdralevich, C. A., Sab, R., Zouhar, Y., and Albertin, G. (2014). *Subsidy Reform in the Middle East and North Africa: Recent Progress and Challenges Ahead*. International Monetary Fund.

Si, S., Adalja, A. A., Gómez, M. I., Lin Lawell, C.-Y. C., and Zhu, C. (2022). Food Safety and Restaurant Food. Working paper, Cornell University.

U.S. Environmental Protection Agency (1994). Automobile Emissions: An Overview. Fact Sheet OMS-5, EPA.

U.S. Environmental Protection Agency (EPA) (2020a). National Ambient Air Quality Standards (NAAQS) for PM. URL: `https://www.epa.gov/pm-pollution/national-ambient-air-quality-standards-naaqs-pm`.

U.S. Environmental Protection Agency (EPA) (2020b). Ozone National Ambient Air Quality Standards (NAAQS). URL: `https://www.epa.gov/ground-level-ozone-pollution/ozone-national-ambient-air-quality-standards-naaqs`.

Wolff, H. (2014). Keep your clunker in the suburb: Low-emission zones and adoption of green vehicles. *The Economic Journal*, 124(578):F481–F512.

World Bank (2016). World Bank Overview of Iran. `http://www.worldbank.org/en/country/iran/overview`. Accessed: 30 December 2016.

Zerbonia, R. and Soraya, B. (1978). Air Pollution Control in Iran. *Journal of the Air Pollution Control Association*, 28(4):334–337.

Zhang, W., Lin Lawell, C.-Y. C., and Umanskaya, V. I. (2017). The Effects of License Plate-Based Driving Restrictions on Air Quality: Theory and Empirical Evidence. *Journal of Environmental Economics and Management*, 82:181–220.

Zhao, X., Luo, D., Lu, K., Wang, X., and Dahl, C. (2019). How the Removal of Producer Subsidies Influences Oil and Gas Extraction: A Case Study in the Gulf of Mexico. *Energy*, 166:1000–1012.

Table 1: Description of the Four Subsidy Reform Events

Subsidy Reform Event	Date	Description
Event 1	June 27, 2007	25% price hike for gasoline and similar price increases for other transportation fuels. This price hike was accompanied by a 60 liter/vehicle monthly quota on gasoline consumption.
Event 2	December 18, 2010	First phase of the Iranian subsidy reform plan implemented, involving significantly higher energy prices (up to 20 times higher) and a decrease in energy subsidies.
Event 3	April 24, 2014	Second phase of the Iranian subsidy reform plan began, involving even higher energy prices. Transportation fuel prices were increased by a higher percentage than natural gas prices were.
Event 4	May 27, 2015	Government further increased transportation fuel prices (but not natural gas prices), and abandoned the quota on gasoline consumption.

Table 2: Summary Statistics for Daily Air Pollution in Tehran, 2007-2017

	Mean	**Std. Dev.**	**Min.**	**Max.**	**N**
Daily average pollution concentration of:					
CO (ppm)	2.948	0.896	0.8	9	3606
O_3 (ppb)	22.998	11.393	1	100	3600
NO_2 (ppb)	50.952	18.708	17.5	184	3606
PM_{10} ($\mu g/m^3$)	84.321	36.516	8	696.5	3606
SO_2 (ppb)	24.179	17.874	1	179.667	3600
Daily maximum pollution concentration of:					
CO (ppm)	5.683	1.962	1.2	17.067	3606
O_3 (ppb)	48.452	25.416	1	191.333	3600
NO_2 (ppb)	77.768	31.293	24	314.75	3606
PM_{10} ($\mu g/m^3$)	144.36	85.671	14.4	2136.923	3606

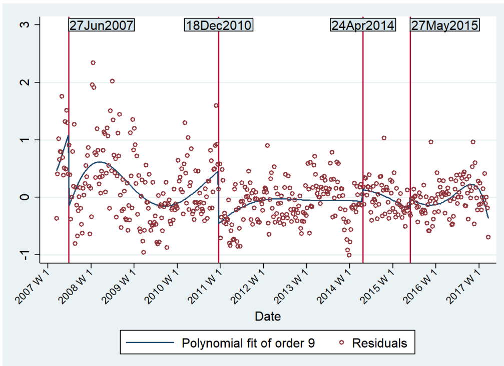
Notes: Daily average pollution concentrations are averaged over all stations in Tehran. Daily maximum pollution concentrations are averaged over all stations in Tehran. *Data source*: Tehran Air Quality Control Company (`http://air.tehran.ir/`).

Table 3: Summary Statistics for Daily Weather in Tehran, 2007-2017

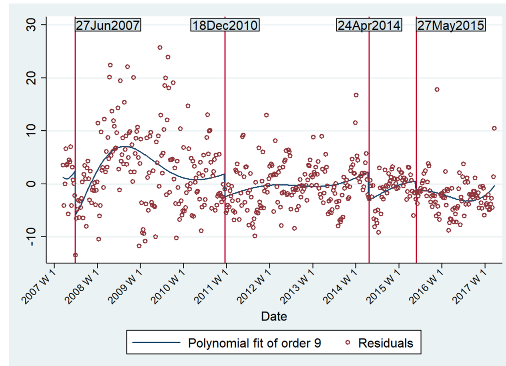
	Mean	**Std. Dev.**	**N**
Daily average temperature (°F)	64.593	18.308	3651
Maximum sustained wind speed (knots)	15.436	5.924	3651

Data source: National Oceanic and Atmospheric Administration (NOAA) (2018)

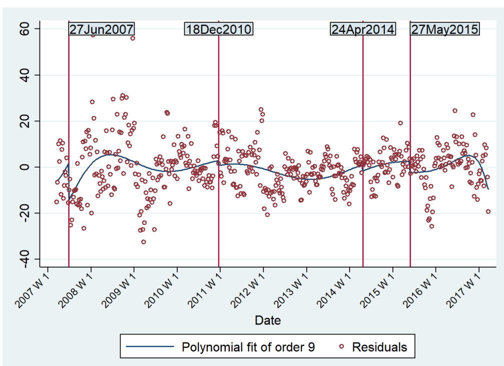
Figure 1: Air Pollution Levels in Tehran, Ninth-Order Polynomial Time Trend, 2007-2017
(Using daily average pollution levels)



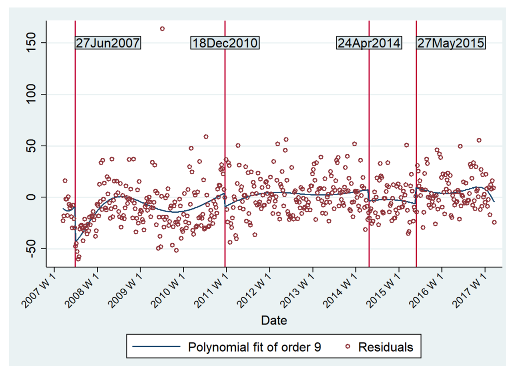
Carbon monoxide (CO)



Ozone (O_3)



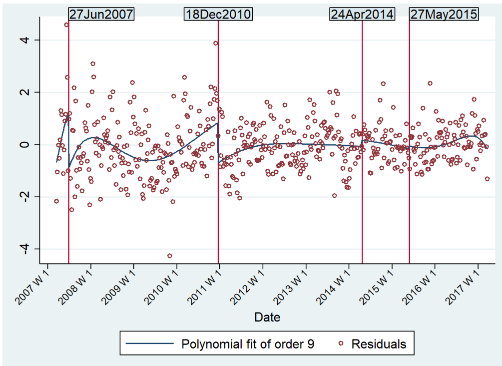
Nitrogen dioxide (NO_2)



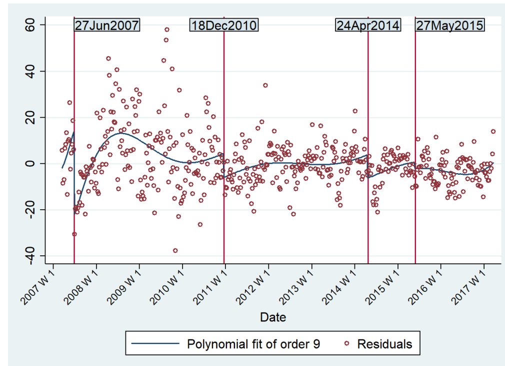
Particulate matter (PM_{10})

Notes: Figure plots residuals from a regression of log daily average pollution concentration levels on weather and seasonality covariates, year effects, and station fixed effects for each of the four air pollutants. The fitted lines are the predicted values of a regression of these residuals on subsidy reform dummies and a ninth-order polynomial time trend. The vertical lines indicate the dates of each of the four subsidy reform events: June 27, 2007; December 18, 2010; April 24, 2014; and May 27, 2015.

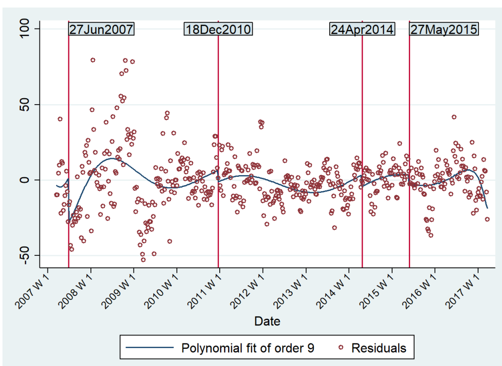
Figure 2: Air Pollution Levels in Tehran, Ninth-Order Polynomial Time Trend, 2007-2017
(Using daily maximum pollution levels)



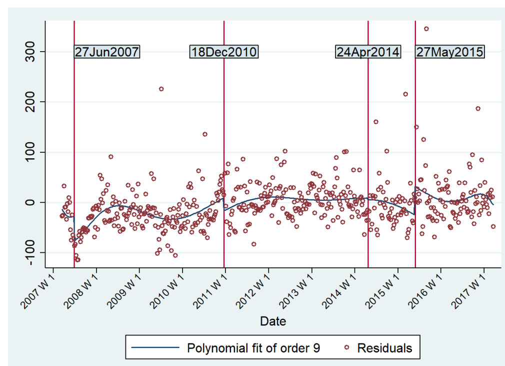
Carbon monoxide (CO)



Ozone (O_3)



Nitrogen dioxide (NO_2)



Particulate matter (PM_{10})

Notes: Figure plots residuals from a regression of log daily maximum pollution concentration levels on weather and seasonality covariates, year effects, and station fixed effects for each of the four air pollutants. The fitted lines are the predicted values of a regression of these residuals on subsidy reform dummies and a ninth-order polynomial time trend. The vertical lines indicate the dates of each of the four subsidy reform events: June 27, 2007; December 18, 2010; April 24, 2014; and May 27, 2015.

Table 4.a: Effects of Subsidy Reform Event 1 on Pollution Levels in Tehran
(with SO_2 as control)

Dependent variable is predicted residuals from regression of log daily avg pollution for:				
	CO	O_3	NO_2	PM_{10}
8 weeks before and after event	-0.0441	-0.3989	-0.2495	-0.5606*
	(0.2626)	(0.1969)	(0.1216)	(0.2097)
10 weeks before and after event	-0.0538	-0.4253	-0.2217	-0.5379
	(0.2148)	(0.1976)	(0.1164)	(0.2245)
20 weeks before and after event	-0.0046	-0.3589	-0.1027	-0.5281*
	(0.1713)	(0.1590)	(0.0893)	(0.1852)
30 weeks before and after event	-0.0450	-0.3121	-0.0614	-0.5714*
	(0.1751)	(0.1661)	(0.0829)	(0.2049)
Dependent variable is predicted residuals from regression of log daily max pollution for:				
	CO	O_3	NO_2	PM_{10}
8 weeks before and after event	-0.2208	-0.6731*	-0.1910	-0.7015*
	(0.3146)	(0.1982)	(0.1891)	(0.2119)
10 weeks before and after event	-0.2551	-0.6931*	-0.1762	-0.6831*
	(0.2358)	(0.2411)	(0.1674)	(0.2205)
20 weeks before and after event	-0.1396	-0.6810*	-0.0129	-0.6182*
	(0.1737)	(0.1969)	(0.0911)	(0.1992)
30 weeks before and after event	-0.1360	-0.6577*	-0.0321	-0.6594*
	(0.1657)	(0.2015)	(0.0976)	(0.1987)

Notes: Each of the cells in this table reports estimates from separate local linear regression discontinuity regressions that each analyze the effect of the first subsidy reform event. Each of the 4 columns presents results for a different pollutant. For each of the 4 pollutants, we run separate local linear regression discontinuity regressions using 4 different windows around the first subsidy reform event of the residual from a first-stage regression of either the log daily average concentration or the log daily maximum concentration of that pollutant on log daily average SO_2, weather and seasonality covariates, year effects, and station fixed effects. Significance code: * indicates significant at a 5% level after applying the Bonferroni correction to adjust for multiple hypothesis testing.

Table 4.b: Effects of Subsidy Reform Event 2 on Pollution Levels in Tehran
(with SO_2 as control)

Dependent variable is predicted residuals from regression of log daily avg pollution for:	CO	O_3	NO_2	PM_{10}
8 weeks before and after event	-0.2207	-0.5050*	-0.0850	0.2613*
	(0.1476)	(0.1667)	(0.1061)	(0.0720)
10 weeks before and after event	-0.1679	-0.2921	-0.0785	0.1482
	(0.1212)	(0.1243)	(0.1019)	(0.0625)
20 weeks before and after event	-0.2071*	-0.3330*	-0.1041	0.0222
	(0.0644)	(0.0920)	(0.0676)	(0.0529)
30 weeks before and after event	-0.1990*	-0.3888*	-0.2137*	0.0368
	(0.0629)	(0.0784)	(0.0414)	(0.0440)

Dependent variable is predicted residuals from regression of log daily max pollution for:	CO	O_3	NO_2	PM_{10}
8 weeks before and after event	-0.3006	-0.5244*	-0.1414	0.3379*
	(0.1640)	(0.1517)	(0.0924)	(0.0986)
10 weeks before and after event	-0.2130	-0.2770	-0.1339	0.0811
	(0.1357)	(0.1254)	(0.0904)	(0.0900)
20 weeks before and after event	-0.1674	-0.4287*	-0.1536	0.0665
	(0.0810)	(0.1015)	(0.0649)	(0.0741)
30 weeks before and after event	-0.2258*	-0.4610*	-0.2094*	0.1209
	(0.0682)	(0.0800)	(0.0387)	(0.0653)

Notes: Each of the cells in this table reports estimates from separate local linear regression discontinuity regressions that each analyze the effect of the second subsidy reform event. Each of the 4 columns presents results for a different pollutant. For each of the 4 pollutants, we run separate local linear regression discontinuity regressions using 4 different windows around the second subsidy reform event of the residual from a first-stage regression of either the log daily average concentration or the log daily maximum concentration of that pollutant on log daily average SO_2, weather and seasonality covariates, year effects, and station fixed effects. Significance code: * indicates significant at a 5% level after applying the Bonferroni correction to adjust for multiple hypothesis testing.

Table 4.c: Effects of Subsidy Reform Event 3 on Pollution Levels in Tehran
(with SO_2 as control)

Dependent variable is predicted residuals from regression of log daily avg pollution for:				
	CO	O_3	NO_2	PM_{10}
8 weeks before and after event	0.0918	0.1329	0.1860	-0.0941
	(0.1588)	(0.1002)	(0.2429)	(0.2386)
10 weeks before and after event	0.0185	0.1189	0.1850	-0.1112
	(0.1207)	(0.0975)	(0.2092)	(0.2335)
20 weeks before and after event	-0.0153	0.0607	0.1829	0.0242
	(0.1031)	(0.0987)	(0.1634)	(0.1669)
30 weeks before and after event	0.0137	-0.0190	0.1430	0.1803
	(0.0849)	(0.0678)	(0.1396)	(0.1123)
Dependent variable is predicted residuals from regression of log daily max pollution for:				
	CO	O_3	NO_2	PM_{10}
8 weeks before and after event	0.0248	0.1190	0.2518	-0.0242
	(0.1878)	(0.0913)	(0.2205)	(0.1843)
10 weeks before and after event	0.0598	0.1045	0.2266	0.0247
	(0.1307)	(0.0914)	(0.1869)	(0.1699)
20 weeks before and after event	0.0417	0.0523	0.1419	0.0934
	(0.1151)	(0.0920)	(0.1290)	(0.1315)
30 weeks before and after event	0.0605	-0.0724	0.2052	0.1274
	(0.1016)	(0.0634)	(0.1470)	(0.1008)

Notes: Each of the cells in this table reports estimates from separate local linear regression discontinuity regressions that each analyze the effect of the third subsidy reform event. Each of the 4 columns presents results for a different pollutant. For each of the 4 pollutants, we run separate local linear regression discontinuity regressions using 4 different windows around the third subsidy reform event of the residual from a first-stage regression of either the log daily average concentration or the log daily maximum concentration of that pollutant on log daily average SO_2, weather and seasonality covariates, year effects, and station fixed effects. Significance code: * indicates significant at a 5% level after applying the Bonferroni correction to adjust for multiple hypothesis testing.

Table 4.d: Effects of Subsidy Reform Event 4 on Pollution Levels in Tehran (with SO_2 as control)

Dependent variable is predicted residuals from regression of log daily avg pollution for:				
	CO	O_3	NO_2	PM_{10}
8 weeks before and after event	0.0361	-0.1912	-0.1513	0.5497*
	(0.0780)	(0.1260)	(0.1518)	(0.1344)
10 weeks before and after event	-0.0427	-0.2043	-0.1695	0.5523*
	(0.0602)	(0.0875)	(0.1459)	(0.1371)
20 weeks before and after event	-0.0517	-0.2525*	-0.1061	0.3552*
	(0.0487)	(0.0798)	(0.0821)	(0.0985)
30 weeks before and after event	-0.0791	-0.2617*	-0.1160	0.1488*
	(0.0425)	(0.0666)	(0.0646)	(0.0586)
Dependent variable is predicted residuals from regression of log daily max pollution for:				
	CO	O_3	NO_2	PM_{10}
8 weeks before and after event	0.1346	-0.2226*	-0.1694	0.3801
	(0.1140)	(0.0878)	(0.1226)	(0.1724)
10 weeks before and after event	0.0799	-0.1774	-0.1292	0.2156
	(0.0952)	(0.1292)	(0.1341)	(0.0993)
20 weeks before and after event	-0.0260	-0.3423*	-0.1116	0.1255
	(0.0736)	(0.0755)	(0.0764)	(0.0956)
30 weeks before and after event	-0.0895	-0.3714*	-0.1204	0.2195*
	(0.0547)	(0.0684)	(0.0597)	(0.0815)

Notes: Each of the cells in this table reports estimates from separate local linear regression discontinuity regressions that each analyze the effect of the fourth subsidy reform event. Each of the 4 columns presents results for a different pollutant. For each of the 4 pollutants, we run separate local linear regression discontinuity regressions using 4 different windows around the fourth subsidy reform event of the residual from a first-stage regression of either the log daily average concentration or the log daily maximum concentration of that pollutant on log daily average SO_2, weather and seasonality covariates, year effects, and station fixed effects. Significance code: * indicates significant at a 5% level after applying the Bonferroni correction to adjust for multiple hypothesis testing.

Table 5.a: Effects of Subsidy Reform Event 1 on Pollution Levels in Tehran (bootstrap)

	Dependent variable is predicted residuals from regression of:			
	log daily avg pollution for:		log daily max pollution for:	
	CO	O_3	CO	O_3
10 weeks before and after event	0.0906	-0.4516	-0.0233	-0.7891
	(0.1168)	(0.2792)	(0.2564)	(0.3711)
20 weeks before and after event	0.0125	-0.5018*	-0.1521	-0.9236
	(0.5996)	(0.0931)	(0.1917)	(0.4596)
30 weeks before and after event	0.0140	-0.5265*	-0.1508	-0.8935*
	(0.1179)	(0.1010)	(0.1865)	(0.1028)

Notes: Each of the cells in this table reports estimates from separate local linear regression discontinuity regressions that each analyze the effect of the first subsidy reform event. Each of the 4 columns presents results for the residualized values of a different dependent variable. For each of the 4 dependent variables, we run separate local linear regression discontinuity regressions using 3 different windows around the first subsidy reform event of the residual from a first-stage regression of that dependent variable on weather and seasonality covariates, year effects, and station fixed effects. Standard errors are bootstrapped over both stages of the estimation, and are in parentheses. Significance code: * indicates significant at a 5% level after applying the Bonferroni correction to adjust for multiple hypothesis testing.

Table 5.b: Effects of Subsidy Reform Event 2 on Pollution Levels in Tehran (bootstrap)

	Dependent variable is predicted residuals from regression of:			
	log daily avg pollution for:		log daily max pollution for:	
	CO	O_3	CO	O_3
10 weeks before and after event	-0.0540	-0.1297	-0.1012	-0.0158
	(0.0691)	(0.1049)	(0.1021)	(0.1401)
20 weeks before and after event	-0.0766	-0.2776*	-0.1698	-0.1463
	(0.0851)	(0.1196)	(0.1405)	(0.0951)
30 weeks before and after event	-0.2700*	-0.2693	-0.1732	-0.3207*
	(0.1196)	(0.1338)	(0.1926)	(0.0926)

Notes: Each of the cells in this table reports estimates from separate local linear regression discontinuity regressions that each analyze the effect of the second subsidy reform event. Each of the 4 columns presents results for the residualized values of a different dependent variable. For each of the 4 dependent variables, we run separate local linear regression discontinuity regressions using 3 different windows around the second subsidy reform event of the residual from a first-stage regression of that dependent variable on weather and seasonality covariates, year effects, and station fixed effects. Standard errors are bootstrapped over both stages of the estimation, and are in parentheses. Significance code: * indicates significant at a 5% level after applying the Bonferroni correction to adjust for multiple hypothesis testing.

Table 5.c: Effects of Subsidy Reform Event 3 on Pollution Levels in Tehran (bootstrap)

Dependent variable is predicted residuals from regression of:				
	log daily avg pollution for:		log daily max pollution for:	
	CO	O_3	CO	O_3
10 weeks before and after event	0.1071	-0.0666	-0.0100	0.1806
	(0.1273)	(0.2687)	(0.2151)	(0.0835)
20 weeks before and after event	0.1081	-0.0341	0.1251	0.1926
	(0.0603)	(0.1936)	(0.1415)	(0.1752)
30 weeks before and after event	0.1490*	0.0284	0.1395	0.0701
	(0.0502)	(0.1469)	(0.1140)	(0.1235)

Notes: Each of the cells in this table reports estimates from separate local linear regression discontinuity regressions that each analyze the effect of the third subsidy reform event. Each of the 4 columns presents results for the residualized values of a different dependent variable. For each of the 4 dependent variables, we run separate local linear regression discontinuity regressions using 3 different windows around the third subsidy reform event of the residual from a first-stage regression of that dependent variable on weather and seasonality covariates, year effects, and station fixed effects. Standard errors are bootstrapped over both stages of the estimation, and are in parentheses. Significance code: * indicates significant at a 5% level after applying the Bonferroni correction to adjust for multiple hypothesis testing.

Table 5.d: Effects of Subsidy Reform Event 4 on Pollution Levels in Tehran (bootstrap)

Dependent variable is predicted residuals from regression of:				
	log daily avg pollution for:		log daily max pollution for:	
	CO	O_3	CO	O_3
10 weeks before and after event	0.0436	-0.3381*	-0.0092	-0.3262*
	(0.0289)	(0.0703)	(0.0728)	(0.1048)
20 weeks before and after event	0.0351	-0.0315	-0.0334	-0.2756*
	(0.0651)	(0.1255)	(0.0662)	(0.0725)
30 weeks before and after event	-0.0199	-0.1067	-0.0410	-0.2999*
	(0.0824)	(0.1040)	(0.0942)	(0.0816)

Notes: Each of the cells in this table reports estimates from separate local linear regression discontinuity regressions that each analyze the effect of the fourth subsidy reform event. Each of the 4 columns presents results for the residualized values of a different dependent variable. For each of the 4 dependent variables, we run separate local linear regression discontinuity regressions using 3 different windows around the fourth subsidy reform event of the residual from a first-stage regression of that dependent variable on weather and seasonality covariates, year effects, and station fixed effects. Standard errors are bootstrapped over both stages of the estimation, and are in parentheses. Significance code: * indicates significant at a 5% level after applying the Bonferroni correction to adjust for multiple hypothesis testing.

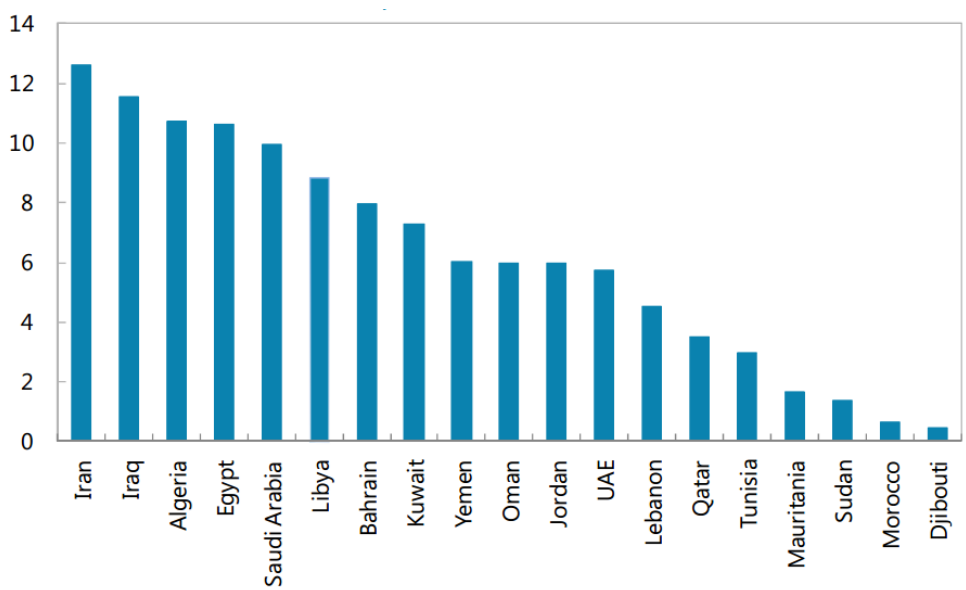
Table 6: Effects of Removing Subsidies on Pollution Levels in Tehran
(bootstrap with SO_2 as control)

	Dependent variable is predicted residuals from regression of:	
	log daily avg CO	log daily max CO
30 weeks before and after Event 1	0.0320	-0.1455
	(0.0884)	(0.2416)
30 weeks before and after Event 2	-0.4201*	-0.4270*
	(0.1787)	(0.1864)
30 weeks before and after Event 3	0.1942	0.4186
	(0.8389)	(0.2134)
30 weeks before and after Event 4	0.0313	-0.0431
	(0.0730)	(0.0918)

Notes: Each of the cells in this table reports estimates from separate local linear regression discontinuity regressions. Each of the 2 columns presents results for the residualized values of a different dependent variable. For each of the 2 dependent variables and each of the 4 subsidy reform events, we run separate local linear regression discontinuity regressions using a window of 30 weeks before and after that subsidy reform event of the residual from a first-stage regression of that dependent variable on log daily average SO_2, weather and seasonality covariates, year effects, and station fixed effects. Standard errors are bootstrapped over both stages of the estimation, and are in parentheses. Significance code: * indicates significant at a 5% level after applying the Bonferroni correction to adjust for multiple hypothesis testing.

Appendix A. Supplementary Tables and Figures

Figure A-1: Energy Subsidies in Middle East and North Africa, 2011



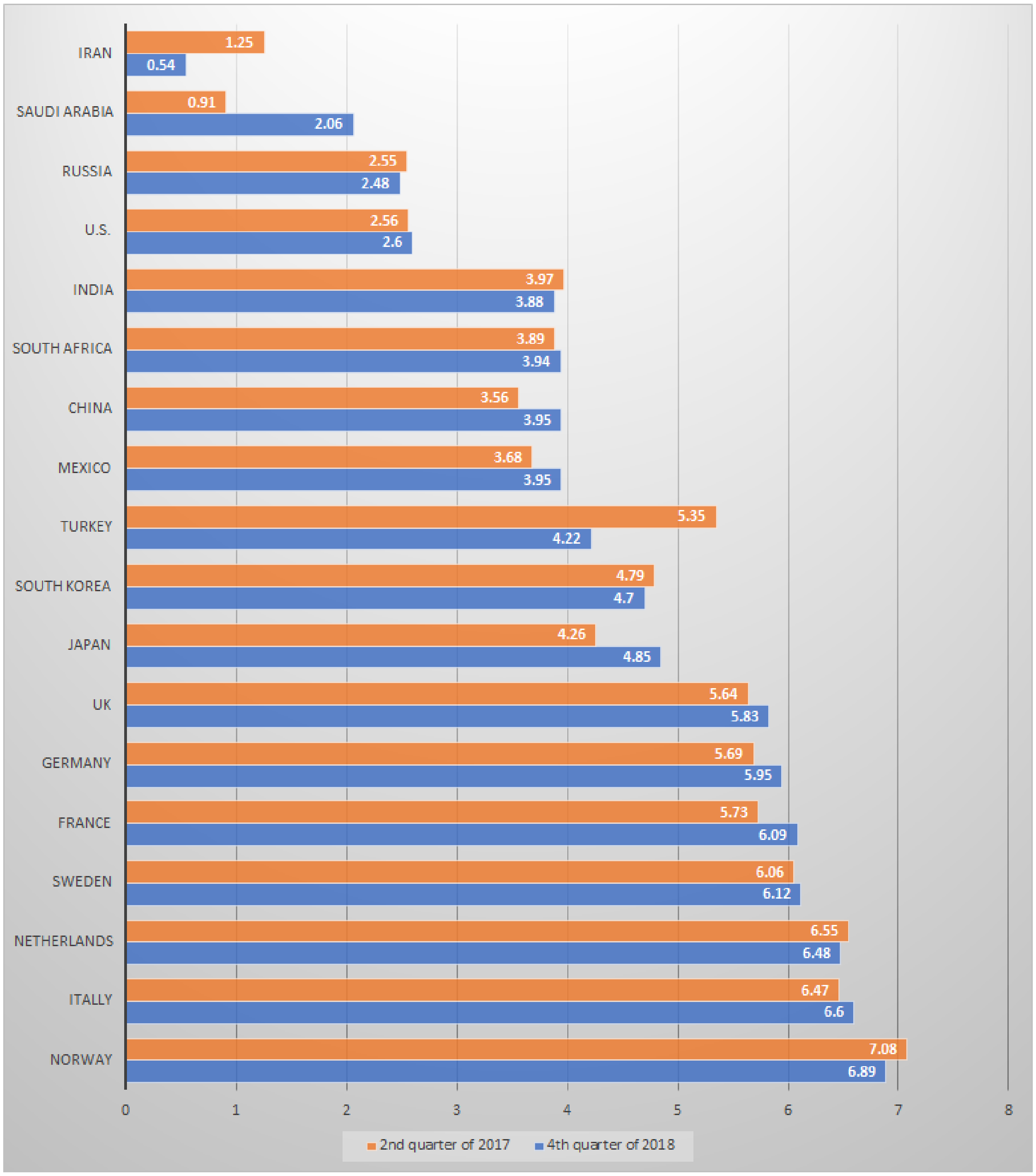
Notes: Figure plots pre-tax energy subsidies (including subsidies on petroleum, electricity, natural gas, and coal) in 2011 as a percentage of GDP for countries in the Middle East and North Africa. *Data source:* Sdralevich et al. (2014).

Table A-1: Energy and Utility Prices in Iran During the Subsidy Reform

Subsidized fuel/utility:	Unit for price	Event 1 6/27/2007	Event 2 12/18/2010	Event 3 4/24/2014	Event 4 5/27/2015
Gasoline	10 IRR per ℓ	100 (400)	400 (700)	700 (1000)	1000
Premium gas	10 IRR per ℓ	150	500 (800)	800 (1100)	1200
Diesel fuel	10 IRR per ℓ	16.5	150 (350)	250 (500)	300
Kerosene	10 IRR per ℓ	16.5	100	150	150
Mazut (Fuel oil)	10 IRR per ℓ	9.5	200	250	300
Aviation fuel	10 IRR per ℓ	100	400	500	600
LPG (Liquefied Petroleum Gas)	10 IRR per kg	5.7	180	210	230
LNG (Liquefied Natural Gas)	10 IRR per kg	40	540	650	
CNG (Compressed natural gas)	10 IRR per m^3	40	300	450	
Natural gas (residential) Winter	10 IRR per m^3	13.2	70	20% increase	
Natural gas (residential) Summer	10 IRR per m^3	13.2	120	20% increase	
Electricity (residential)	10 IRR per kWh	12.9	45-75	24% increase	
Water (residential)	10 IRR per m^3	127	262.3	20% increase	

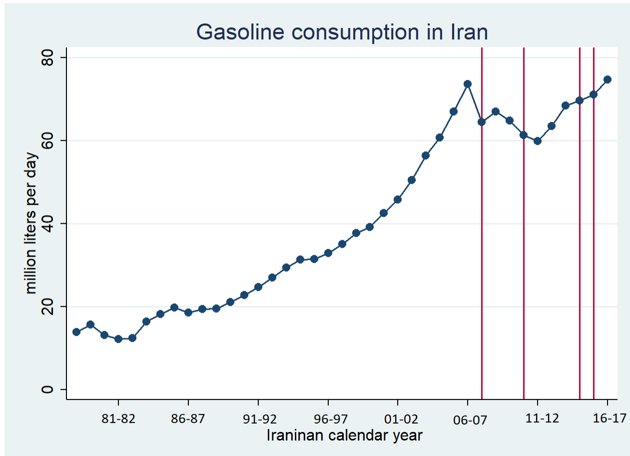
Notes: Table reports the energy and utility prices implemented at each subsidy reform event. Prices are in 10 Iranian Rial (IRR). Values inside parentheses are prices for volumes exceeding the 60 liter (ℓ) quota. *Source:* Kheiravar (2019).

Figure A-2: Global Gasoline Prices, 2017-2018



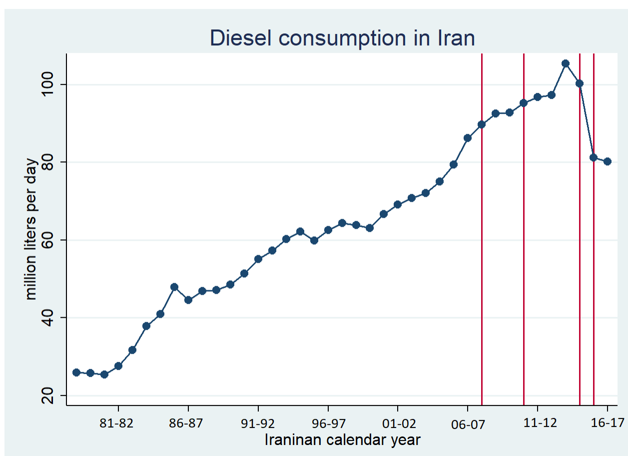
Notes: Figure plots global gasoline prices (in U.S. dollars per gallon) in 2017 and 2018. *Data source:* ?.

Figure A-3: Annual Gasoline Consumption in Iran, 1978-2017



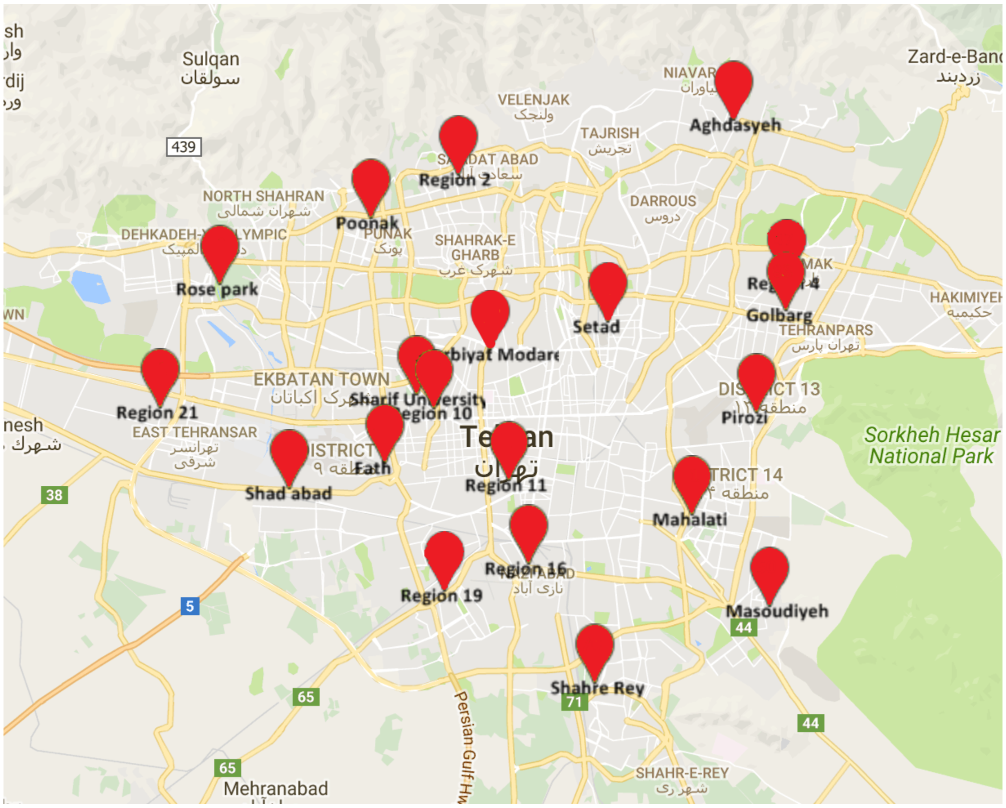
Data source: National Iranian Oil Refining and Distribution Company (`niordc.ir`)

Figure A-4: Annual Diesel Consumption in Iran, 1978-2017



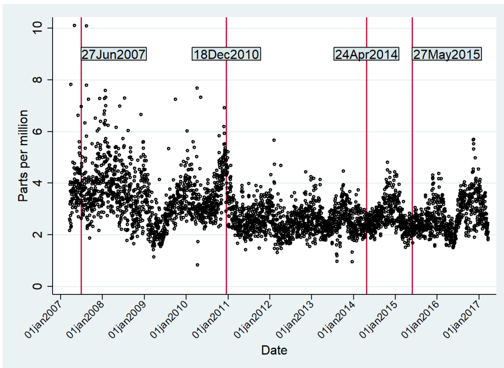
Data source: National Iranian Oil Refining and Distribution Company (`niordc.ir`)

Figure A-5: Local Air Quality Monitoring Stations in Tehran

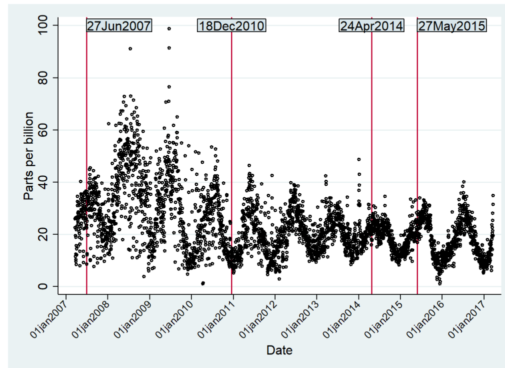


Note: Map shows the 24 local air quality monitoring stations in Tehran.
Data source: Tehran Air Quality Control Company (`http://air.tehran.ir/`).

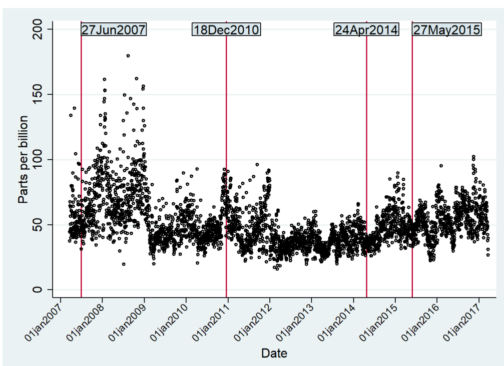
Figure A-6: Mean Daily Air Pollution Levels in Tehran, 2007-2017



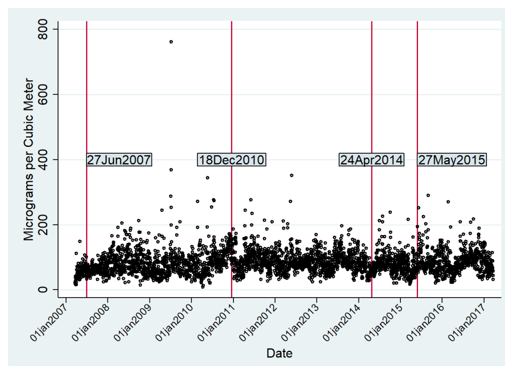
Carbon monoxide (CO)



Ozone (O_3)



Nitrogen dioxide (NO_2)



Particulate matter (PM_{10})

Notes: Figure plots mean daily pollution levels for each of the four pollutants for the time period 1997 to 2009. Mean daily pollution levels are constructed by averaging the hourly mean concentration over all hours in a day and over all monitoring stations. The vertical lines indicate the dates of each of the four subsidy reform events: June 27, 2007; December 18, 2010; April 24, 2014; and May 27, 2015.

Table A-2.a: Effects of Subsidy Reform Event 1 on Pollution Levels in Tehran

Dependent variable is predicted residuals from regression of log daily avg pollution for:	CO	O_3	NO_2	PM_{10}
8 weeks before and after event	-0.0400	-0.4243	-0.2661*	-0.5540*
	(0.2738)	(0.1864)	(0.0903)	(0.2119)
10 weeks before and after event	-0.0102	-0.4790*	-0.2210	-0.5456
	(0.2252)	(0.1627)	(0.0894)	(0.2259)
20 weeks before and after event	-0.0504	-0.3942*	0.0213	-0.2359
	(0.1515)	(0.1473)	(0.0832)	(0.1196)
30 weeks before and after event	-0.0564	-0.3517	-0.0149	-0.4396*
	(0.1576)	(0.1434)	(0.0869)	(0.1560)
Dependent variable is predicted residuals from regression of log daily max pollution for:	CO	O_3	NO_2	PM_{10}
8 weeks before and after event	-0.2804	-0.7085*	-0.2355	-0.7877*
	(0.2038)	(0.2075)	(0.1666)	(0.2225)
10 weeks before and after event	-0.2299	-0.7851*	-0.2060	-0.7365*
	(0.1839)	(0.2129)	(0.1626)	(0.2245)
20 weeks before and after event	-0.1555	-0.6346*	0.0054	-0.5550*
	(0.1356)	(0.1608)	(0.1030)	(0.1705)
30 weeks before and after event	-0.1695	-0.6043*	-0.0389	-0.6388*
	(0.1352)	(0.1588)	(0.1066)	(0.1957)

Notes: Each of the cells in this table reports estimates from separate local linear regression discontinuity regressions that each analyze the effect of the first subsidy reform event. Each of the 4 columns presents results for a different pollutant. For each of the 4 pollutants, we run separate local linear regression discontinuity regressions using 4 different windows around the first subsidy reform event of the residual from a first-stage regression of either the log daily average concentration or the log daily maximum concentration of that pollutant on weather and seasonality covariates, year effects, and station fixed effects. Significance code: * indicates significant at a 5% level after applying the Bonferroni correction to adjust for multiple hypothesis testing.

Table A-2.b: Effects of Subsidy Reform Event 2 on Pollution Levels in Tehran

Dependent variable is predicted residuals from regression of log daily avg pollution for:				
	CO	O_3	NO_2	PM_{10}
8 weeks before and after event	-0.1424	-0.3042	-0.1714	0.1004
	(0.1135)	(0.1446)	(0.1094)	(0.1835)
10 weeks before and after event	-0.1457	-0.0793	-0.1681	-0.0477
	(0.1146)	(0.1180)	(0.1089)	(0.1237)
20 weeks before and after event	-0.0420	-0.1486	-0.0893	0.0777
	(0.0817)	(0.0806)	(0.0589)	(0.1053)
30 weeks before and after event	-0.0973	-0.1584	-0.0494	0.1912
	(0.0548)	(0.0728)	(0.0568)	(0.0911)

Dependent variable is predicted residuals from regression of log daily max pollution for:				
	CO	O_3	NO_2	PM_{10}
8 weeks before and after event	-0.1710	-0.2160	-0.2403*	0.1065
	(0.1264)	(0.1393)	(0.0885)	(0.1802)
10 weeks before and after event	-0.1804	-0.0819	-0.2488*	-0.0115
	(0.1313)	(0.1280)	(0.0893)	(0.1398)
20 weeks before and after event	-0.0322	-0.1649	-0.1503*	0.0842
	(0.0854)	(0.0914)	(0.0525)	(0.1157)
30 weeks before and after event	-0.1290	-0.1589	-0.1079	0.1841
	(0.0560)	(0.0835)	(0.0507)	(0.0925)

Notes: Each of the cells in this table reports estimates from separate local linear regression discontinuity regressions that each analyze the effect of the second subsidy reform event. Each of the 4 columns presents results for a different pollutant. For each of the 4 pollutants, we run separate local linear regression discontinuity regressions using 4 different windows around the second subsidy reform event of the residual from a first-stage regression of either the log daily average concentration or the log daily maximum concentration of that pollutant on weather and seasonality covariates, year effects, and station fixed effects. Significance code: * indicates significant at a 5% level after applying the Bonferroni correction to adjust for multiple hypothesis testing.

Table A-2.c: Effects of Subsidy Reform Event 3 on Pollution Levels in Tehran

Dependent variable is predicted residuals from regression of log daily avg pollution for:	CO	O_3	NO_2	PM_{10}
8 weeks before and after event	0.0785	0.1393	0.1070	-0.2400
	(0.1195)	(0.1148)	(0.1266)	(0.1381)
10 weeks before and after event	0.1574	0.1261	0.1169	-0.2487
	(0.0850)	(0.1097)	(0.1053)	(0.1353)
20 weeks before and after event	0.0951	0.0882	0.1078	-0.0498
	(0.0600)	(0.0841)	(0.0989)	(0.0798)
30 weeks before and after event	0.0690	0.1058	0.0509	-0.0684
	(0.0504)	(0.0677)	(0.0802)	(0.0731)
Dependent variable is predicted residuals from regression of log daily max pollution for:	CO	O_3	NO_2	PM_{10}
8 weeks before and after event	0.0384	0.2325	0.2229	-0.2303
	(0.1446)	(0.1083)	(0.1314)	(0.1411)
10 weeks before and after event	0.1767	0.2333	0.1957	-0.1272
	(0.0963)	(0.1084)	(0.1175)	(0.1150)
20 weeks before and after event	0.1136	0.1553	0.1915	-0.0599
	(0.0683)	(0.0817)	(0.1048)	(0.0856)
30 weeks before and after event	0.0974	0.1782	0.1108	-0.0722
	(0.0585)	(0.0739)	(0.0799)	(0.0772)

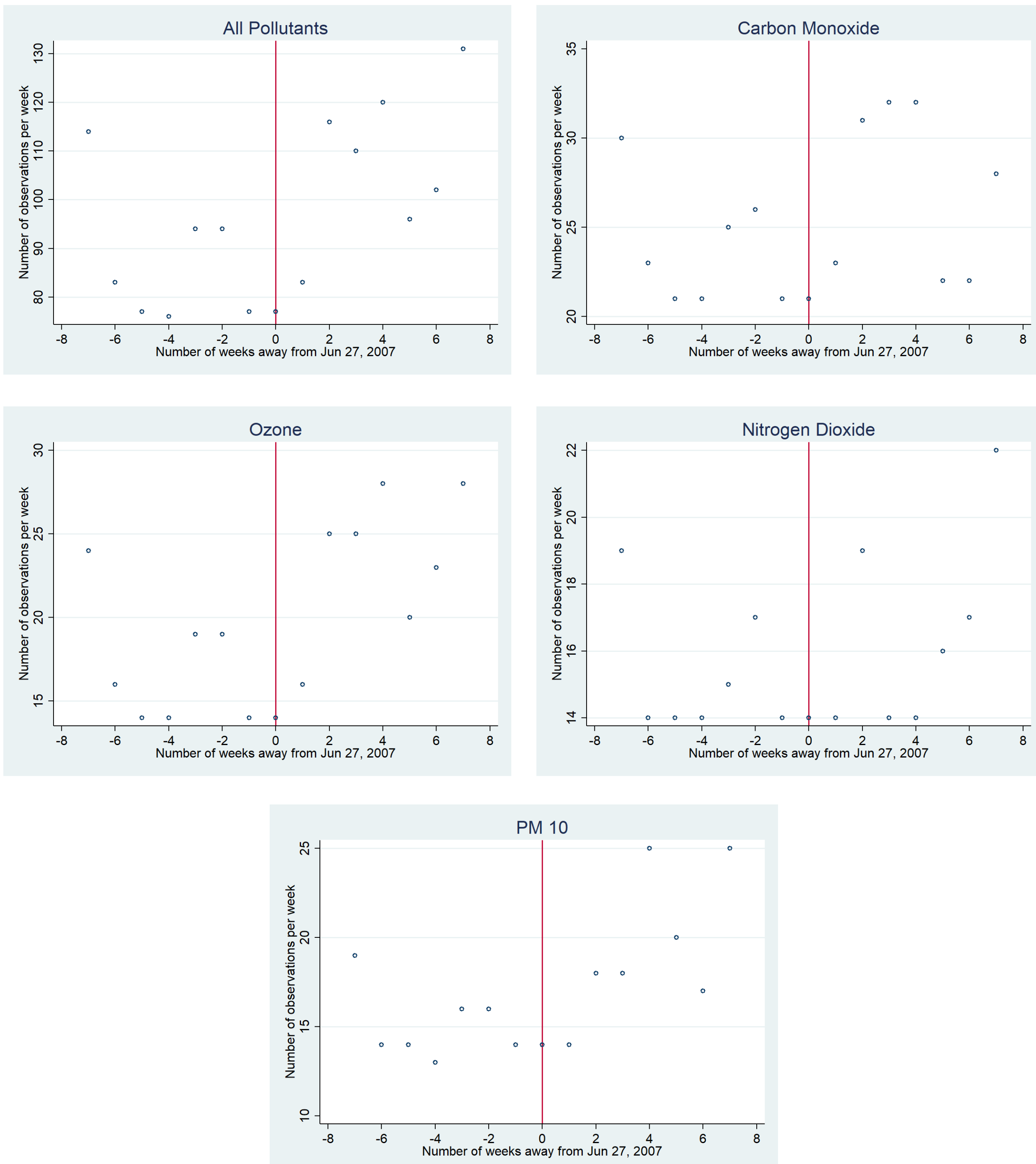
Notes: Each of the cells in this table reports estimates from separate local linear regression discontinuity regressions that each analyze the effect of the third subsidy reform event. Each of the 4 columns presents results for a different pollutant. For each of the 4 pollutants, we run separate local linear regression discontinuity regressions using 4 different windows around the third subsidy reform event of the residual from a first-stage regression of either the log daily average concentration or the log daily maximum concentration of that pollutant on weather and seasonality covariates, year effects, and station fixed effects. Significance code: * indicates significant at a 5% level after applying the Bonferroni correction to adjust for multiple hypothesis testing.

Table A-2.d: Effects of Subsidy Reform Event 4 on Pollution Levels in Tehran

Dependent variable is predicted residuals from regression of log daily avg pollution for:	CO	O_3	NO_2	PM_{10}
8 weeks before and after event	0.1133	-0.2013	0.0353	0.4661*
	(0.0830)	(0.1080)	(0.1591)	(0.1222)
10 weeks before and after event	0.0011	-0.1854	-0.0958	0.4871*
	(0.0606)	(0.0779)	(0.1373)	(0.1218)
20 weeks before and after event	-0.0170	-0.2232*	-0.1249	0.3949*
	(0.0502)	(0.0718)	(0.0742)	(0.0922)
30 weeks before and after event	-0.0605	-0.1905*	-0.1464	0.0846
	(0.0398)	(0.0551)	(0.0622)	(0.0461)
Dependent variable is predicted residuals from regression of log daily max pollution for:	**CO**	**O_3**	**NO_2**	**PM_{10}**
8 weeks before and after event	0.1572	-0.1297	-0.0449	0.3390
	(0.1048)	(0.0901)	(0.1351)	(0.1526)
10 weeks before and after event	0.0660	-0.1291	-0.0741	0.0625
	(0.0830)	(0.1113)	(0.1293)	(0.0805)
20 weeks before and after event	0.0130	-0.2921*	-0.1402	0.0966
	(0.0696)	(0.0600)	(0.0632)	(0.0823)
30 weeks before and after event	-0.0782	-0.2254*	-0.1589*	0.1164
	(0.0481)	(0.0497)	(0.0560)	(0.0728)

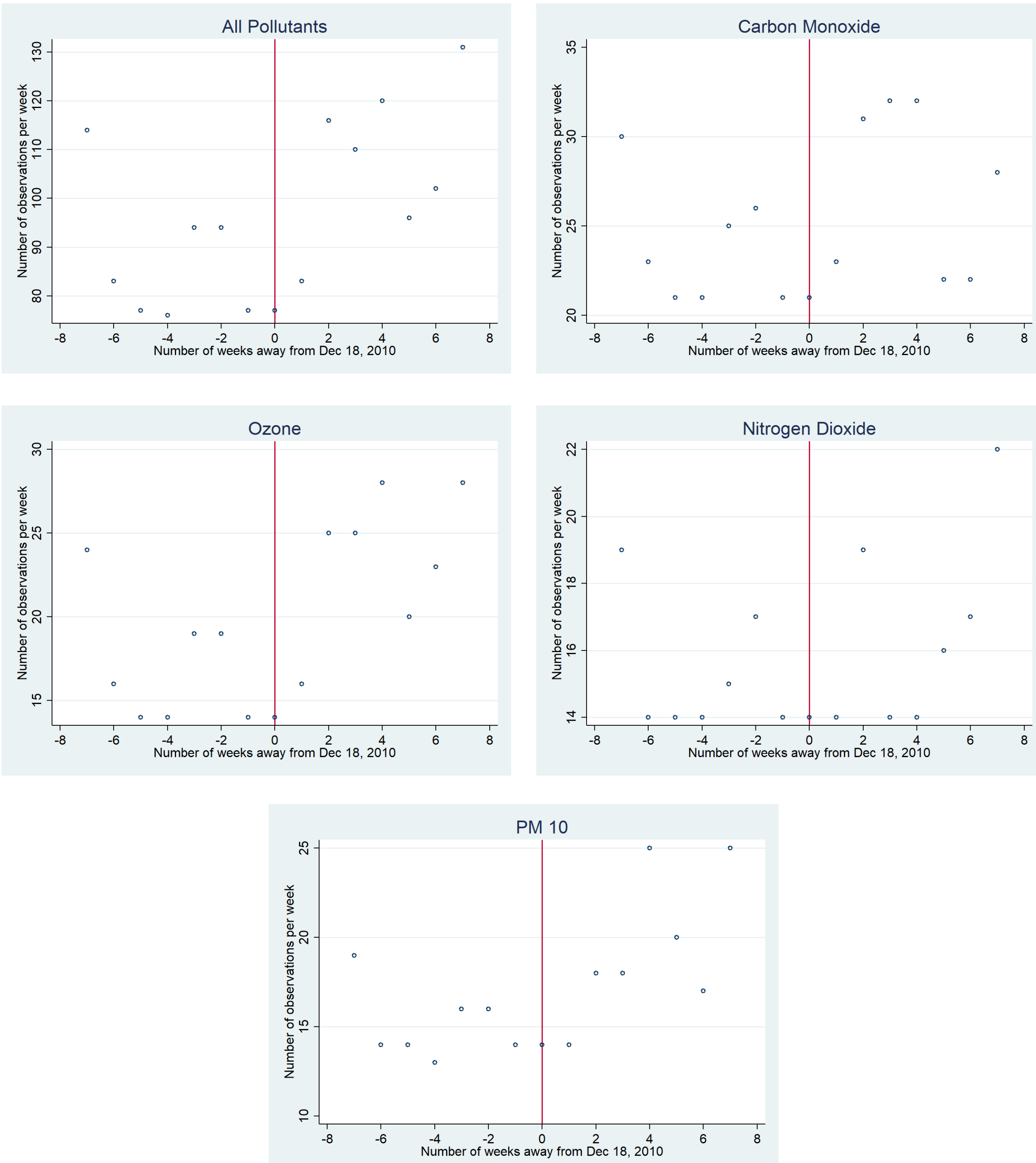
Notes: Each of the cells in this table reports estimates from separate local linear regression discontinuity regressions that each analyze the effect of the fourth subsidy reform event. Each of the 4 columns presents results for a different pollutant. For each of the 4 pollutants, we run separate local linear regression discontinuity regressions using 4 different windows around the fourth subsidy reform event of the residual from a first-stage regression of either the log daily average concentration or the log daily maximum concentration of that pollutant on weather and seasonality covariates, year effects, and station fixed effects. Significance code: * indicates significant at a 5% level after applying the Bonferroni correction to adjust for multiple hypothesis testing.

Figure A-7: Number of Observations per Week for Each Pollutant Around Event 1



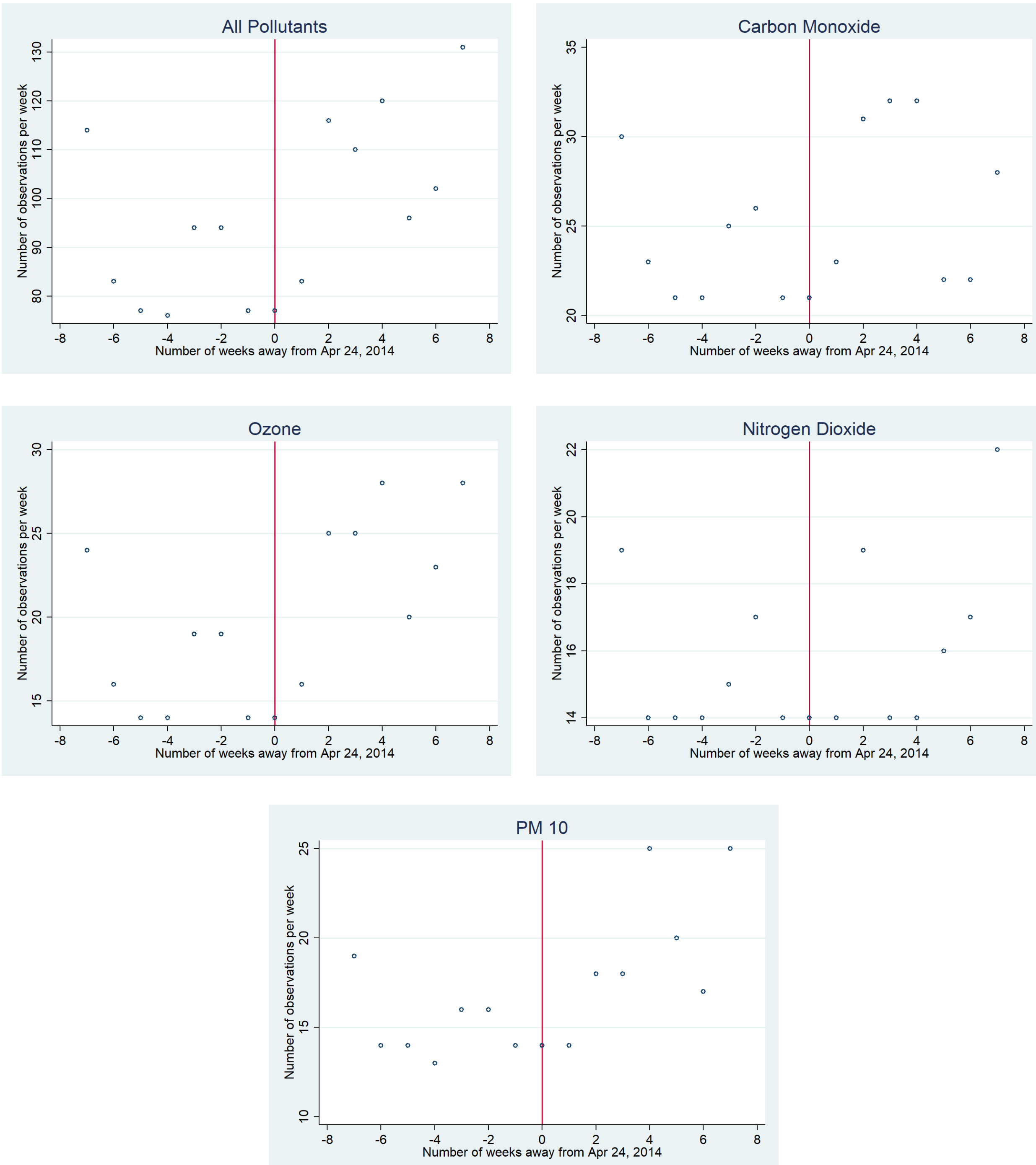
Note: To examine the distribution of the forcing variable (time) at the threshold (the implementation of the first event of the subsidy reform on June 27, 2007), this figure plots the number of observations per week against the week away from June 27, 2007 for each pollutant.

Figure A-8: Number of Observations per Week for Each Pollutant Around Event 2



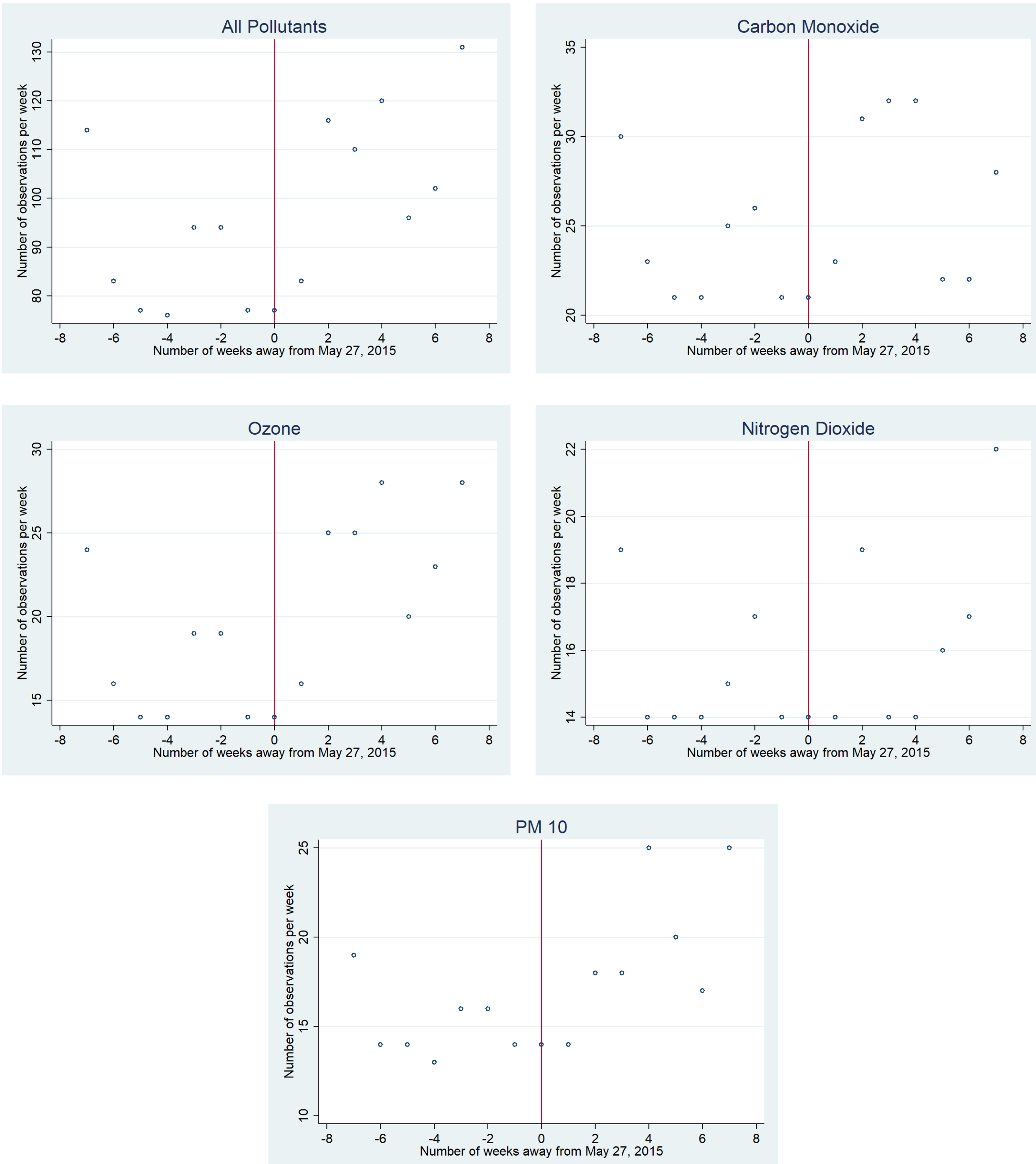
Note: To examine the distribution of the forcing variable (time) at the threshold (the implementation of the second event of the subsidy reform on December 18, 2010), this figure plots the number of observations per week against the week away from December 18, 2010 for each pollutant.

Figure A-9: Number of Observations per Week for Each Pollutant Around Event 3



Note: To examine the distribution of the forcing variable (time) at the threshold (the implementation of the third event of the subsidy reform on April 24, 2014), this figure plots the number of observations per week against the week away from April 24, 2014 for each pollutant.

Figure A-10: Number of Observations per Week for Each Pollutant Around Event 4



Note: To examine the distribution of the forcing variable (time) at the threshold (the implementation of the fourth event of the subsidy reform on May 27, 2015), this figure plots the number of observations per week against the week away from May 27, 2015 for each pollutant.

Table A-3: Effects of Removing Subsidies on Daily Mean Temperature in Tehran

Dependent variable is log daily average temperature					
N^{th} order time trend:	10^{th} order	9^{th} order	8^{th} order	7^{th} order	6^{th} order
Event 1: June 27, 2007	0.0077	0.0077	-0.0017	-0.0017	-0.0034
	(0.0742)	(0.0742)	(0.0738)	(0.0738)	(0.0734)
Event 2: December 18, 2010	-0.0666	-0.0666	-0.0692	-0.0692	-0.0712
	(0.0762)	(0.0762)	(0.0762)	(0.0762)	(0.0756)
Event 3: April 24, 2014	-0.0303	-0.0303	-0.0321	-0.0321	-0.0353
	(0.0789)	(0.0789)	(0.0789)	(0.0789)	(0.0774)
Event 4: May 27, 2015	-0.0092	-0.0092	-0.0016	-0.0016	-0.0056
	(0.0851)	(0.0851)	(0.0848)	(0.0848)	(0.0826)

Notes: Table reports estimates from a regression discontinuity model with a N^{th}-order time trend. All models include day of the week, month of the year, and year dummies. The unit of observation is a station-day. The reported coefficients correspond to indicator variables that equal to one for every day during the time periods of the respective subsidy reform phase. Standard errors, in parentheses, are robust to heteroskedasticity. Significance code: * indicates significant at a 5% level.

Table A-4: Effects of Removing Subsidies on Daily Maximum Wind Speed in Tehran

Dependent variable is log daily maximum sustained wind speed					
N^{th} order time trend:	10^{th} order	9^{th} order	8^{th} order	7^{th} order	6^{th} order
Event 1: June 27, 2007	-0.1304	-0.1304	-0.1052	-0.1052	-0.1180
	(0.1986)	(0.1986)	(0.1976)	(0.1976)	(0.1964)
Event 2: December 18, 2010	-0.0225	-0.0225	-0.0157	-0.0157	-0.0310
	(0.2040)	(0.2040)	(0.2040)	(0.2040)	(0.2023)
Event 3: April 24, 2014	0.0201	0.0201	0.0250	0.0250	0.0008
	(0.2112)	(0.2112)	(0.2112)	(0.2112)	(0.2072)
Event 4: May 27, 2015	0.1011	0.1011	0.0808	0.0808	0.0500
	(0.2277)	(0.2277)	(0.2271)	(0.2271)	(0.2210)

Notes: Table reports estimates from a regression discontinuity model with a N^{th}-order time trend. All models include day of the week, month of the year, and year dummies. The unit of observation is a station-day. The reported coefficients correspond to indicator variables that equal to one for every day during the time periods of the respective subsidy reform phase. Standard errors, in parentheses, are robust to heteroskedasticity. Significance code: * indicates significant at a 5% level.

Appendix B. Placebo Tests

To examine the robustness of our results, we run placebo tests for each of our regression discontinuity regression models using placebo subsidy reform dates instead of the actual subsidy reform dates as the treatment. If we do not find significant treatment effects where there has been no treatment, then this means that our results are robust to our tests.

Since the implementation of the first event of the subsidy reform on June 27, 2007 took place on the fourth Wednesday of the month, we choose as our placebo date for the first subsidy reform event a fourth Wednesday prior to the first event of the subsidy reform: Wednesday, March 28, 2007. For the placebo test of the first event of the subsidy reform, we use data from before the first subsidy reform event only (i.e., before June 27, 2007).

Since the implementation of the second event of the subsidy reform on December 18, 2010 took place on the third Saturday of the month, we choose as our placebo dates for the second subsidy reform event a third Saturdays of the month, and, following Imbens and Lemieux (2008), one that was roughly in the middle of the relevant sample period between the first and second subsidy events: Saturday, June 21, 2008. For the placebo test of the second event of the subsidy reform, we use data from after the first subsidy reform event but before the second subsidy reform event only (i.e., after June 27, 2007 but before December 18, 2010).

Since the implementation of the third event of the subsidy reform on April 24, 2014 took place on the fourth Thursday of the month, we choose as our placebo date for the third subsidy reform event a fourth Thursday, and, following Imbens and Lemieux (2008), one that was roughly in the middle of the relevant sample period between the second and third subsidy events: Thursday, June 27, 2013. For the placebo test of the third event of the subsidy reform, we use data from after the second subsidy reform event but before the third subsidy reform event only (i.e., after December 18, 2010 but before April 24, 2014).

Since the implementation of the fourth event of the subsidy reform on May 27, 2015 took place on the fourth Wednesday of the month, we choose as our placebo date for the fourth subsidy reform event a fourth Wednesday of the month, and, following Imbens and Lemieux (2008), one that was roughly in the middle of the relevant sample period between the third and fourth subsidy events: Wednesday, November 19, 2014. For the placebo test of the fourth event of the subsidy reform, we use data from after the third subsidy reform event but before the fourth subsidy reform event only (i.e., after April 24, 2014 but before May 27, 2015).

We run placebo tests of the local linear regression discontinuity regressions with robust confidence intervals for windows ranging from 8 to 30 weeks before and after each respective placebo subsidy reform event date in Tables B-1.a-B-1.d. Results of the placebo tests show that none of the placebo treatment effects are significant and negative for any of the pollutants, and that the few placebo treatment effects that are statistically significant at a 5% level are positive, not negative. Thus, since we do not find any significant negative treatment effects where there has been no treatment, and since we find very few significant treatment effects where there has been no treatment, this means that our results are robust to our tests.

Table B-1.a: Effects of Placebo Subsidy Reform Event 1 on Pollution Levels in Tehran

Dependent variable is predicted residuals from regression of log daily avg pollution for:	CO	O_3	NO_2	PM_{10}
8 weeks before and after event	0.0391	0.1906	-0.0549	-0.0434
	(0.1972)	(0.2187)	(0.3087)	(0.3401)
10 weeks before and after event	-0.0498	0.2756	-0.1187	-0.0851
	(0.1742)	(0.2213)	(0.2786)	(0.3014)
20 weeks before and after event	-0.2343	0.3323	-0.2428	-0.2437
	(0.1536)	(0.1856)	(0.2511)	(0.2736)
30 weeks before and after event	-0.2349	0.3626	-0.2947	
	(0.1539)	(0.1761)	(0.2475)	(0.2671)

Dependent variable is predicted residuals from regression of log daily max pollution for:	CO	O_3	NO_2	PM_{10}
8 weeks before and after event	0.2506	0.0166	0.0479	-0.1141
	(0.2212)	(0.4022)	(0.3294)	(0.3239)
10 weeks before and after event	0.0833	0.2110	-0.0200	-0.1627
	(0.1959)	(0.3384)	(0.3001)	(0.2919)
20 weeks before and after event	-0.3343	0.4222	-0.1355	-0.4169
	(0.1495)	(0.2836)	(0.2767)	(0.2592)
30 weeks before and after event	-0.2758	0.4499	-0.1561	-0.3781
	(0.1484)	(0.2630)	(0.2767)	(0.2528)

Notes: Table presents results of placebo tests using a placebo subsidy reform date (March 28, 2007) instead of the actual subsidy reform date for the first subsidy reform event. Each of the cells in this table reports estimates from separate local linear regression discontinuity regressions. Each of the 4 columns presents results for a different pollutant. For each of the 4 pollutants, we run separate local linear regression discontinuity regressions using 4 different windows around the placebo subsidy reform date for the first subsidy reform event of the residual from a first-stage regression of either the log daily average concentration or the log daily maximum concentration of that pollutant on weather and seasonality covariates, year effects, and station fixed effects. Significance code: * indicates significant at a 5% level after applying the Bonferroni correction to adjust for multiple hypothesis testing.

Table B-1.b: Effects of Placebo Subsidy Reform Event 2 on Pollution Levels in Tehran

Dependent variable is predicted residuals from regression of log daily avg pollution for:				
	CO	O_3	NO_2	PM_{10}
8 weeks before and after event	-0.3626	0.0655	0.0593	0.3397
	(0.1763)	(0.1672)	(0.1285)	(0.1721)
10 weeks before and after event	-0.3727	0.0547	0.0468	0.2120
	(0.1656)	(0.2102)	(0.1297)	(0.1308)
20 weeks before and after event	0.0128	0.0269	0.0975	-0.0527
	(0.1024)	(0.1270)	(0.0992)	(0.0853)
30 weeks before and after event	0.0493	0.0271	0.1026	-0.0309
	(0.0919)	(0.1071)	(0.0991)	(0.0768)

Dependent variable is predicted residuals from regression of log daily max pollution for:				
	CO	O_3	NO_2	PM_{10}
8 weeks before and after event	-0.2260	0.0228	0.1192	0.1823
	(0.2032)	(0.2630)	(0.2068)	(0.1867)
10 weeks before and after event	-0.2226	0.0153	0.0771	-0.0158
	(0.1719)	(0.2807)	(0.1823)	(0.1274)
20 weeks before and after event	0.0213	0.0493	0.1075	-0.0277
	(0.1089)	(0.1546)	(0.1181)	(0.1025)
30 weeks before and after event	0.0338	0.0463	0.0714	0.0202
	(0.0860)	(0.1311)	(0.1112)	(0.0859)

Notes: Table presents results of placebo tests using a placebo subsidy reform date (June 21, 2008) instead of the actual subsidy reform date for the second subsidy reform event. Each of the cells in this table reports estimates from separate local linear regression discontinuity regressions. Each of the 4 columns presents results for a different pollutant. For each of the 4 pollutants, we run separate local linear regression discontinuity regressions using 4 different windows around the placebo subsidy reform date for the second subsidy reform event of the residual from a first-stage regression of either the log daily average concentration or the log daily maximum concentration of that pollutant on weather and seasonality covariates, year effects, and station fixed effects. Significance code: * indicates significant at a 5% level after applying the Bonferroni correction to adjust for multiple hypothesis testing.

Table B-1.c: Effects of Placebo Subsidy Reform Event 3 on Pollution Levels in Tehran

Dependent variable is predicted residuals from regression of log daily avg pollution for:	CO	O_3	NO_2	PM_{10}
8 weeks before and after event	0.2663*	0.1274	0.2175	0.4197*
	(0.0843)	(0.0973)	(0.0920)	(0.0747)
10 weeks before and after event	0.2933*	0.1258	0.2294	0.4145*
	(0.0813)	(0.0973)	(0.0944)	(0.0732)
20 weeks before and after event	0.0338	0.1231	0.1378	0.4462*
	(0.0365)	(0.0990)	(0.0836)	(0.0676)
30 weeks before and after event	0.0726	0.0863	0.0632	0.4560*
	(0.0406)	(0.0828)	(0.0728)	(0.0685)

Dependent variable is predicted residuals from regression of log daily max pollution for:	CO	O_3	NO_2	PM_{10}
8 weeks before and after event	0.2742*	0.1089	0.2857*	0.3769*
	(0.0840)	(0.1006)	(0.0942)	(0.0812)
10 weeks before and after event	0.2795*	0.1061	0.3000*	0.3730*
	(0.0831)	(0.1006)	(0.0994)	(0.0810)
20 weeks before and after event	0.3075*	0.1055	0.0394	0.3709*
	(0.0594)	(0.1017)	(0.0681)	(0.0761)
30 weeks before and after event	0.1301*	0.0590	0.1446	0.4033*
	(0.0457)	(0.0863)	(0.0783)	(0.0810)

Notes: Table presents results of placebo tests using a placebo subsidy reform date (January 31, 2013) instead of the actual subsidy reform date for the third subsidy reform event. Each of the cells in this table reports estimates from separate local linear regression discontinuity regressions. Each of the 4 columns presents results for a different pollutant. For each of the 4 pollutants, we run separate local linear regression discontinuity regressions using 4 different windows around the placebo subsidy reform date for the third subsidy reform event of the residual from a first-stage regression of either the log daily average concentration or the log daily maximum concentration of that pollutant on weather and seasonality covariates, year effects, and station fixed effects. Significance code: * indicates significant at a 5% level after applying the Bonferroni correction to adjust for multiple hypothesis testing.

Table B-1.d: Effects of Placebo Subsidy Reform Event 4 on Pollution Levels in Tehran

Dependent variable is predicted residuals from regression of log daily avg pollution for:				
	CO	O_3	NO_2	PM_{10}
8 weeks before and after event	0.2829	0.2351	0.1102	-0.1749
	(0.1210)	(0.1247)	(0.2588)	(0.1600)
10 weeks before and after event	0.3336*	0.2086	0.2327	-0.2276
	(0.0942)	(0.1105)	(0.1975)	(0.1482)
20 weeks before and after event	0.3601*	0.1736	0.1484	-0.1417
	(0.0904)	(0.0859)	(0.1458)	(0.1078)
30 weeks before and after event	0.3131*	0.0781	0.0239	0.2366*
	(0.0717)	(0.0595)	(0.1015)	(0.0632)

Dependent variable is predicted residuals from regression of log daily max pollution for:				
	CO	O_3	NO_2	PM_{10}
8 weeks before and after event	0.3843	0.1287	0.2225	-0.0096
	(0.1622)	(0.1647)	(0.2771)	(0.1688)
10 weeks before and after event	0.4097*	0.1285	0.3253	0.1006
	(0.1276)	(0.1549)	(0.2193)	(0.2077)
20 weeks before and after event	0.4656*	0.2211	0.1961	0.2591*
	(0.1105)	(0.1009)	(0.1616)	(0.0995)
30 weeks before and after event	0.4484*	0.1236	-0.0096	0.2759*
	(0.0947)	(0.0677)	(0.0986)	(0.0719)

Notes: Table presents results of placebo tests using a placebo subsidy reform date (July 16, 2014) instead of the actual subsidy reform date for the fourth subsidy reform event. Each of the cells in this table reports estimates from separate local linear regression discontinuity regressions. Each of the 4 columns presents results for a different pollutant. For each of the 4 pollutants, we run separate local linear regression discontinuity regressions using 4 different windows around the placebo subsidy reform date for the fourth subsidy reform event of the residual from a first-stage regression of either the log daily average concentration or the log daily maximum concentration of that pollutant on weather and seasonality covariates, year effects, and station fixed effects. Significance code: * indicates significant at a 5% level after applying the Bonferroni correction to adjust for multiple hypothesis testing.