Social Benefits and Private Costs of Driving Restriction Policies: The Impact of Madrid Central on Congestion, Pollution and Consumer Spending*

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Abstract

Low Emission Zones are defined areas within a city where driving restrictions are introduced with the aim to reduce pollution, but they may also unintentionally distort consumer spending decisions. By increasing transportation costs to ban-affected areas, driving restrictions could discourage spending in stores of those areas. This paper empirically evaluates the effects of a driving restriction regulation in Madrid, Spain, known as Madrid Central. First, using a difference-in-differences identification strategy, we find an immediate decrease of 19 percent in pollution and of 16 percent in congestion with pollution dropping further once fines were levied. Second, we rely on credit card transaction data to show consumers affected by the regulation reduced their brick-and-mortar spending in the regulated area by 20 percent. Finally, we find suggestive evidence that e-commerce may smooth the impact of changes in transportation costs due to environmental regulations as affected consumers partially substitute their consumption spending from brick-and-mortar to online shopping.

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1 Introduction

By now, there is wide consensus both within and outside economics that air pollution is harmful to people's health. While part of the literature establishes the causal link between air pollution and health outcomes (e.g. Chay and Greenstone, 2003), much ongoing research also studies the consequences of air pollution beyond health outcomes. In fact, bad air quality has been associated with less cognitive development (Bharadwaj et al., 2017), lower educational and schooling attainment (Ebenstein et al., 2016), crime (Carrillo et al., 2018), or lower productivity (Chang et al., 2016), among others.[1] Given the evidence, it is not surprising that high air pollution levels across the globe have driven the implementation of a wide array of policies and regulations at different levels of government.

Our paper contributes to the policy debate on the social benefits and the distribution of costs of such environmental policies. High pollution levels are the result of differences between the social and private marginal cost. As a result, environmental policies aim to bring private marginal cost of pollution closer to the social levels and achieve socially optimal levels of pollution.

A typical policy to decrease pollution and improve local air quality are traffic restrictions, which are an example of drastic command-and-control regulations with unevenly distributed costs and benefits. While traffic restriction regulations have been found to be effective and reduce outpatient visits (Simeonova et al., 2019), ambulance calls (Zhong et al., 2017), hospitalizations and mortality (He et al., 2019), and pharmaceutical expenditures (Rohlf et al., 2020), we know little on the indirect effect of these policies on economic activity. Indeed, a reduction in economic activity may change the perception of these pollution-reducing policies by the public. On the one hand, measuring the costs on economic activity allows regulators and policy makers to determine the net gain of implementing these policies. On the other hand, the implementation of these policies may affect different stakeholders differently by spatially redistributing economic activity and potentially generating a division between winners and losers. In other words, fixing a local pollution hot spot might require measures that impose drastic costs borne by few individuals but generate benefits for many others. In fact, the costs incurred by a few under such policies may be informative of the reduction in deadweight loss associated with the correction of pollution externalities. This

[1] The list of outcomes potentially affected by air pollution goes beyond those listed here and reaches out to infant mortality and other health outcomes in the developing world (Currie and Neidell, 2005; Deryugina et al., 2019; Greenstone and Hanna, 2014; Greenstone and Jack, 2015; Hammitt and Zhou, 2006; Neidell, 2004).

paper contributes to the discussion of the costs of environmental regulation by evaluating the impact of a driving ban implemented in downtown Madrid, known as Madrid Central, on traffic congestion, air pollution, and economic activity.

Madrid Central ("MC" hereafter) is a Low Emission Zone in the city center of Madrid aiming to reduce air pollution through a decline in traffic congestion, and to raise air quality to European Union standards. To achieve this goal, the regulation restricts entry of cars in the center of the city of Madrid (a zone that we will refer to as "MC area" hereafter) to people living elsewhere. This policy raises a stark tradeoff. Lower emissions and lower traffic congestion in the city center will be a direct benefit of these regulations. However, by restricting access by car, transportation and transaction costs are likely to increase for those consumers living outside the MC area, potentially discouraging consumption and retail sales in businesses within the MC area. In other words, pollution and congestion levels were higher than socially desirable prior to the implementation of MC because private citizens and local businesses were not paying for the externality they generated in terms of pollution and congestion. The MC policy and regulation increases the cost of economic activity while correcting the amount of pollution and congestion closer to socially optimal levels. Our paper empirically examines and documents this tradeoff between cleaner air and lower retail sales in two distinct sections.

First, using data from the European Environmental Agency and the city of Madrid on air quality and vehicle traffic, we assess the direct effect of the regulation on air pollution and traffic congestion in downtown Madrid relative to other areas within the city and its greater metropolitan area. We use difference-in-difference specifications to estimate the effect of MC on congestion and pollution where the MC area zip codes are treated and the period post-MC is the treatment period. Our findings show significant decreases in traffic volume and air pollution in the MC area zip codes relative to other areas in Madrid. In particular, we find that during the first months of implementation, the number of cars per hour in the MC area decreased by 16.1% and the concentration of nitrogen dioxide (NO_2), a harmful pollutant, decreased by 18.6% in the MC area. Moreover, we find suggestive evidence of a reduction in traffic in close-by areas in the short run. Once monetary fines were levied from drivers violation MC regulations, NO_2 dropped further to more than 41% below its pre MC-levels.

Second, we use data on brick-and-mortar and online credit card transactions to evaluate changes in retail spending within the MC area before and after the implementation of MC. These data on consumer spending span from the first week of 2015 to the last week of June of 2019, while MC was introduced in the first week of December 2018. The data set is unique in that it details the date of each transaction, the zip code of residence of the credit card owner (buyer's zip code) and the zip code of the selling establishment (seller's zip code). We aggregate this information weekly for each buyer zip code–seller zip code pair. As a result, we can effectively measure "trade flows" between all zip codes within the metropolitan area of Madrid before and after the introduction of MC.

We use a triple differences identification strategy in a gravity model, exploiting the fact that MC only has a direct impact on those buyers who live outside the MC area and make all or part of their purchases in the center of Madrid. Following this strategy, we are able to estimate the impact of MC on consumers traveling to downtown Madrid to do their shopping both (1) relative to the shopping of these same consumers in other areas of the city not directly affected by MC, and (2) relative to the shopping in the MC area of consumers living within the MC area, as they are effectively exempt from the MC regulation. The exceptional granularity of our data allows us to mitigate threats to identification by estimating a very demanding specification that controls for time-varying supply and demand shocks in specific areas of the city.

We find a 20.6% decrease in the value of brick-and-mortar spending and a 12.1% increase in the value of online spending of buyers residing in zip codes outside the MC area in establishments within the MC area. This finding opens the possibility of a policy debate linking environmental and e-commerce regulation that favors e-commerce adoption by consumers, retail establishments and small and medium-sized enterprises. Furthermore, we find that zip codes with higher levels of household income, zip codes with higher number of cars per person, and zip codes with worse access to public transportation reduce their spending in the MC area more than other zip codes. Overall, these heterogeneity results are consistent with the MC policy increasing transportation costs and therefore being the channel through which the policy is able to reduce pollution and congestion in the targeted area.

Although a large number of papers investigate the health and air quality benefits of different versions of driving bans and low emission zones, only a few papers study the effects on economic outcomes such as labor supply decisions and local commerce. Most recently, Blackman et al. (2018) and Blackman et al. (2020) use the contingent valuation method based on surveys in Mexico City and Beijing to estimate the costs faced by drivers due to driving restriction programs. Viard and Fu (2015) is the closest paper to ours. The authors show that traffic restriction policies in Beijing reduced the number of hours of labor supplied by affected workers. Besides these works, research on the impact of driving bans on economic outcomes is almost nonexistent. Our paper differs from the aforementioned in a number of ways. First, we present a well-founded and comprehensive empirical analysis of the impact of a traffic restriction on economic activity. Second, our credit card transaction data allow us to measure economic activity in a robust manner as trade flows between zip codes within Madrid. Third, identification relies on a well-defined triple difference strategy where we utilize geographical variation in the application of the policy within the city of Madrid. Fourth and last, our data allow us to separate brick-and-mortar from online transactions. Therefore, we are also able to demonstrate that the diffusion and adoption of e-commerce may dilute part of the potentially negative impact of pollution-reducing policies on retail sales.

Our findings also contribute to a sound literature on the causes and consequences of air pollution, as well as that on the optimization and evaluation of pollution-reduction policies (see reviews and papers by Parry et al., 2007; Graff Zivin and Neidell, 2013; Currie and Walker, 2011, 2019). We examine a particular type of policy aiming to reduce traffic congestion and air pollution by limiting the number of cars allowed to circulate in a heavily congested part of a city. Madrid is not the first city to implement a program of this nature, and consequently ours is not the first study evaluating the efficiency and efficacy of such environmental policies. However, compared to other policies, Madrid Central is extremely restrictive and affects the vast majority of vehicles in the city.

The effectiveness of transportation policies in reducing pollution varies substantially across cities. Barahona et al. (2020) note that unsuccessful programs typically place uniform restrictions on drivers through license plate-based restrictions while vintage-specific restrictions are effective because they directly restrict the access of the most polluting cars. Indeed, license plate-based restrictions in Mexico City (Eskeland and Feyzioglu, 1997; Davis, 2008; Salas, 2010; Gallego et al., 2013; Oliva, 2015), Bogotá (Zhang et al., 2017), Beijing (Chen et al., 2013; Viard and Fu, 2015; Zhong et al., 2017), and other Chinese cities (Lin et al., 2011; Ye, 2017) failed to improve, or even worsened, air quality.[2] In contrast, vintage-specific measures taken in Santiago de Chile (Rivera, 2017; Barahona et al., 2020) or many German cities (Wolff, 2014; Gehrsitz, 2017; Pestel and Wozny, 2021) restrict access based on emissions and have been highly effective. The vintage-

[2] In the case of Quito (Carrillo et al., 2016) and San José – Costa Rica (Osakwe, 2010) the evidence is less clear.

specific policy we study in this paper, Madrid Central, is of the same nature but has a much stronger bite as it affects at least 70% of the vehicles registered in the city of Madrid alone, plus all other vehicles driving from outside the city.[3]

We view our findings as novel within the existing literature, and important for policy evaluation and future policy design. On the one hand, our results confirm that pollution-reducing policies aiming at traffic control can be effective. They also corroborate the notion that restrictions on the extensive margin that affect the type of car driven can improve air quality substantially and that highly restrictive transportation policies can be highly beneficial for air quality.

On the other hand, our analysis considers the impact of pollution-reducing policies on economic activity clearly identifying winners and losers. As a side result, our findings regarding the role of e-commerce attenuating potential backfire of some of these policies on economic activity. An implication of our results is that combining environmental friendly policies with regulation that helps retail and small and medium-sized enterprises transition from brick-and-mortar to e-commerce could be socially beneficial. Our results are also informative about the role that e-commerce may play in shaping consumption spending and competition patterns in modern cities.

The structure of the paper is as follows. Section 2 describes in detail the regulation. In Section 3, we describe the data. Section 4 evaluates whether the regulation was effective in reducing traffic congestion and pollution in the MC area. Section 5 examines changes in consumption spending patterns due to the introduction of MC. Section 6 concludes.

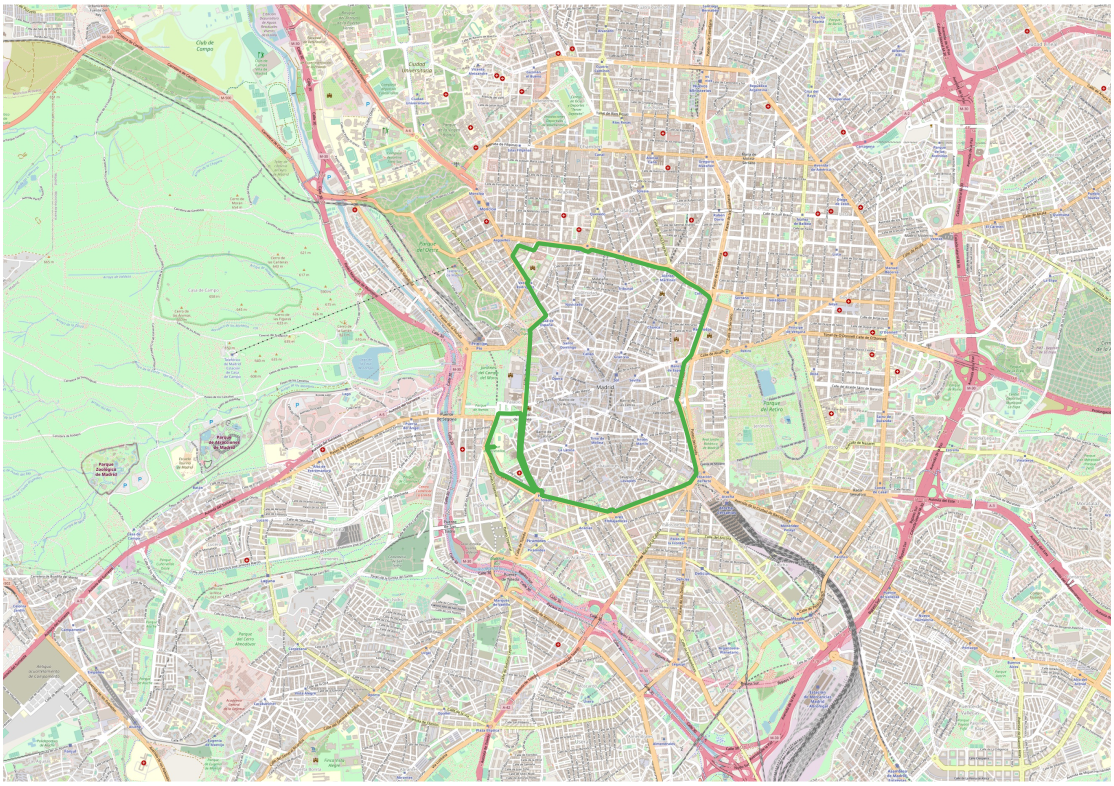
2 Madrid Central

The city council of Madrid, Spain, enacted a city-specific traffic regulation, known as Madrid Central, on November 30, 2018. This regulation restricted access by car to an area of 472 hectares located in the Madrid city center.[4] Figure 1 shows

[3]One could add to this taxonomy a third kind of policy, congestion charges for entering certain areas that have to be paid by (almost) all drivers. These measures have for example been successfully implemented in London (Leape, 2006; Quddus et al., 2007) and Stockholm (Simeonova et al., 2019). Programs that make public transport more attractive also seem to achieve pollution reductions. Evidence from Taipei (Chen and Whalley, 2012) and Beijing (Li et al., 2019) shows that additional subway lines induce city dwellers to substitute from private to public transport.

[4]The city of Madrid has a total surface of 60,400 hectares. The median zip code has a size of 645 hectares.

FIGURE 1: Map of Madrid Central within the City of Madrid



Notes: The green line marks the part of Madrid's city center subject to the regulations of Madrid Central. Source: OpenStreetMap.

the extension of the affected area, which is the historic center of Madrid as well as the main commercial and leisure district of the city.[5]

Although traffic congestion has been a pervasive problem in Madrid, the primary goal of MC was to reduce air pollution from NO_2 in downtown Madrid. Madrid was exceeding NO_2 limit values set by the EU Directive 2008/50/EC. This led the European Commission (2017) to send a "final warning" to the Spanish government as part of its infringement procedures. Facing substantial fines in case of further violation of European law, the city council of Madrid updated its

[5]See Boletin Oficial Ayuntamiento de Madrid (2018) or `https://www.madrid.es/UnidadesDescentralizadas/UDCMovilidadTransportes/AreaCentral/01InfGral/Ac%20Jta%20Gob%2029%20oct%202018_MC.pdf` for details.

clean air plan[6] that eventually introduced Madrid Central, with the explicit goal of reducing air pollution from NO_2.[7]

While limiting traffic should also reduce congestion, we found no evidence that congestion was debated as a particularly relevant issue at that time requiring a response as extreme as MC. Similarly, while other pollutants could also be affected by the policy, they were not at the same concerning levels as NO_2. For example, in our data the highest daily 8-hour maximum of CO is 2.8 mg/m^3, far below the EU's limit value of 10 mg/m^3. This is in stark contrast to the regular violation of NO_2 limit values.

When MC went into effect, local authorities noticeably restricted entry by car to the affected area, so access may only be granted under exceptional circumstances. These exceptions are based on the emission category of vehicles. All vehicles are classified in five different categories: those without environmental certification (hereafter we refer to these as "A" vehicles), B, C, ECO and ZERO, in descending order of emission levels.[8] Accordingly, the city elaborated a number of exceptions that we list as follows:

(i) Residents of the MC area can enter the MC area without restrictions.[9] If they were to buy a new car, it would need to belong to category B or cleaner to enter without restrictions.

(ii) All cars of category B or cleaner can enter if they park in a public or private garage.[10]

(iii) Access of delivery vehicles is subject to time restrictions.

[6] See press release https://www.madrid.es/portales/munimadrid/es/Inicio/Actualidad/Noticias/La-Comision-Europea-avanza-en-el-proceso-de-infraccion-a-Madrid-por-incumplimiento-de-niveles-de-NO2/?vgnextfmt=default&vgnextoid=16aed3936f14a510VgnVCM2000001f4a900aRCRD&vgnextchannel=a12149fa40ec9410VgnVCM100000171f5a0aRCRD

[7] See press release https://www.madrid.es/portales/munimadrid/es/Inicio/El-Ayuntamiento/Todas-las-noticias/Madrid-Central-reducira-en-un-40-la-emision-de-contaminantes-en-el-centro-de-la-ciudad/?vgnextfmt=default&vgnextoid=25e0021e2be74610VgnVCM2000001f4a900aRCRD&vgnextchannel=e40362215c483510VgnVCM2000001f4a900aRCRD

[8] Category ZERO refers to electric and hybrid vehicles with a range of more than 40 km. Category ECO refers to hybrid vehicles with a range of less than 40 km and gas vehicles. Category C refers to gasoline vehicles registered after 2006 (EURO 4, 5 and 6) and diesel vehicles registered after 2014 (EURO 6). Category B refers to gasoline vehicles registered after 2000 (EURO 3) and diesel vehicles registered after 2006 (EURO 4 and 5). Category A comprises all other and unclassified vehicles.

[9] A resident of the MC area was able to invite 20 "A" cars a month previous application for a day permit to the city hall until 2020.

[10] Owners and tenants of private garages need a permit. The plates of vehicles accessing public garages are automatically registered.

(iv) Commercial and industrial vehicles with a parking permit located inside the MC area are allowed to access the MC area. New permits are only handed out for vehicles of category B or cleaner.

(v) People with reduced mobility are not subject to restrictions.

(vi) ZERO emission cars are not subject to restrictions.

(vii) ECO emission cars can enter the MC area and park for a maximum of two hours.

(viii) Taxis and ride-hailing vehicles can enter if they are of category B or cleaner.

(ix) Public transport vehicles are not subject to restrictions.

As a result, the population most affected by these regulations is the non-residents of the MC area with A cars. That segment of the population cannot access the MC area at all with their own vehicles unless invited by a resident of the MC area and issued a corresponding day permit. Non-residents may only enter the MC area if they are to park in a garage if they belong to category B or cleaner. This implies, for instance, that non-residents are not allowed to park in the street or access the MC area to pick up or drop off passengers if their vehicles are not classified as ECO or ZERO. Drivers of an A vehicle are not allowed to drive by the MC area, even when the final destination is outside the MC area.

To quantify the bite of the regulation, we have obtained data from the city of Madrid on all registered cars in 2019 with classifications following the MC policy car classification. According to these data, 91% of vehicles in the city (that is, a total of 1,279,841 vehicles) were registered to individuals (as opposed to firms) living outside the MC area. Out of those, 88.1% (1,126,988) were vehicles of the "A" category and affected by the policy. Not counting commercial vehicles, this means at the very least 70% of all vehicles registered in the city of Madrid were affected by the policy.

The first day of implementation of the MC regulations was November 30, 2018. During its first month, large traffic signals indicated the perimeter of the MC area and the prohibition of entry. Moreover, local police monitored traffic and informed those drivers in violation of the new regulation without imposing any fines. In January 2019, the local authorities introduced an automatic monitoring system based on cameras installed at all access points of the MC area. The system registered license plates and informed violating drivers by postal mail of the infraction, without imposing any fines. From March 16, 2019, violations were fined €90. Our data and analysis cover the period up to June 30, 2019.

After describing in this section the regulation and timing of MC, we proceed with our description of the data we use for our estimation of the impact of MC on traffic congestion, air pollution, and retail sales.

3 Data

To perform our analysis, we combine two different sources of data. First, we use data on traffic, local air pollution, and meteorological conditions. Second, we gain access to proprietary data on weekly credit card spending at the buyer-seller zip code pair level for all zip codes within the metropolitan area of Madrid. While the former data allow us to quantify the direct benefits from the driving ban on traffic congestion and air pollution, the latter data will help us quantify the indirect impact of the driving ban on consumer spending.

We collected these data not only for the MC area but also for the whole metropolitan area of Madrid. Since there is no legal definition for such area, we define it to include: (1) all zip codes within the city of Madrid, and (2) all zip codes at least partially inside a buffer of 5 km around the perimeter of Madrid. We divide the city of Madrid into the MC area and the rest of the city. Overall, the full metropolitan area comprises 122 zip codes (55 within the city of Madrid and 67 outside). As the credit card data span from the first week of 2015 to the last week of June 2019, we obtain all other data for the same period.

3.1 Traffic and pollution data

We obtain traffic data from the Madrid Department of Traffic Technology published through the city's open data portal.[11] The majority of data comes mostly from traffic lights, but also from other types of sensors. The raw data are reported in 15-minute intervals. First, we drop erroneous observations and outliers in the 99.9th percentile. Then, we aggregate each monitor's readings to the daily level if traffic is observed at least 80 times during a given day. Finally, we aggregate all daily monitor data to the weekly level, conditional on observing every day of the week. The resulting dataset is an unbalanced panel of 4,170 traffic monitors across the city of Madrid. Traffic outside Madrid city is unobserved. We determine whether a traffic monitor is located inside or outside the MC area by its exact coordinates.

[11] Retrieved from https://datos.madrid.es/portal/site/egob/menuitem.c05c1f754a33a9fbe4b2e4b284f1a5a0/?vgnextoid=33cb30c367e78410VgnVCM1000000b205a0aRCRD&vgnextchannel=374512b9ace9f310VgnVCM100000171f5a0aRCRD&vgnextfmt=default

Traffic is measured by the number of vehicles per hour and by the share of time (in %) a certain road section is occupied by a vehicle. Summary statistics in Table 1 show that traffic has decreased over time, but more so inside the MC area. Because highway M-30 is a major ring road that helps intercity traffic bypass the center of Madrid as well as connect commuting traffic to reach the city center, a significant number of traffic monitors are purposely located on this major road, which explains the high number of vehicles observed at monitors outside the city center.

Because EU regulation defines limit values on NO_2 and other pollutants,[12] cities are obliged to install air quality monitoring stations. The European Environmental Agency (EEA) collects measures from all member countries and makes them publicly available. There are 33 stations reporting NO_2 levels across the metropolitan area.[13] Again, we determine whether a station is located inside or outside the MC area by its exact coordinates. Importantly, one of these 33 stations is located inside the MC area. We use information from this station to estimate treatment effects, considering the rest of the stations as the control group.

The limit value for the mean annual NO_2 concentration specified by the EU regulation is 40 µg/m^3. As any reading of a station whose daily average is higher than 40 µg/m^3 contributes to the potential violation of this regulation, we create an indicator that takes value one if a station's daily average NO_2 reading exceeds 40 µg/m^3. We aggregate all daily NO_2 readings at the weekly level.

Table 1 summarizes weekly and annual mean NO_2 levels and the percentage share of days with NO_2 exceeding 40 µg/m^3. One can see that NO_2 levels, both at the station inside the MC area and at the stations outside that area, are very high according to EU standards. The daily average concentration inside the MC area is 47 µg/m^3 prior to the introduction of MC, while it is 37 µg/m^3 outside the MC area. We also calculate the share of station-by-year observations that violate the limit value imposed by EU regulation. Table 1 shows that, during the sample period, the station inside the MC area exceeds the limit value every year but after the introduction of MC. Moreover, other stations outside the city center also violate the threshold. This happens in 38% of all observations.

It is worth noting that meteorological conditions can heavily affect air quality. For example, sunlight is a key component in the decomposition of NO_2. It is therefore important to control for local weather conditions when studying determinants

[12]Directive 2008/50/EU. See https://ec.europa.eu/environment/air/quality/standards.htm

[13]Appendix Figure A.1 shows a map with locations of all pollution monitoring stations in Madrid, represented by pink circles.

TABLE 1: Descriptive statistics on traffic and pollution levels

	Mean (1)	SD (2)	Min (3)	Max (4)	Obs (5)
		Pre-MC inside MC area			
Traffic (93 stations)					
Vehicles per hour	343.41	296.98	0.00	1715.28	13,226
Time occupied [%]	11.06	10.23	0.00	98.51	13,222
Pollution (1 station)					
NO_2 [$\mu g/m^3$]	47.20	12.01	27.14	95.69	202
$NO_2 > 40\,\mu g/m^3$	0.65	0.30	0.00	1.00	202
Yearly NO_2 [$\mu g/m^3$]	47.30	2.49	44.38	49.60	4
Yearly $NO_2 > 40\,\mu g/m^3$	1.00	0.00	1.00	1.00	4
		Post-MC inside MC area			
Traffic (93 stations)					
Vehicles per hour	305.97	242.72	26.56	1531.33	1,817
Time occupied [%]	9.45	7.68	0.00	98.50	1,817
Pollution (1 station)					
NO_2 [$\mu g/m^3$]	37.46	16.83	16.03	74.38	29
$NO_2 > 40\,\mu g/m^3$	0.40	0.40	0.00	1.00	29
Yearly NO_2 [$\mu g/m^3$]	35.01	.	35.01	35.01	1
Yearly $NO_2 > 40\,\mu g/m^3$	0.00	.	0.00	0.00	1
		Pre-MC outside MC area			
Traffic (4077 stations)					
Vehicles per hour	455.17	511.13	0.00	4354.98	556,889
Time occupied [%]	6.52	7.29	0.00	98.33	556,638
Pollution (32 stations)					
NO_2 [$\mu g/m^3$]	37.10	16.60	3.82	133.44	6,523
$NO_2 > 40\,\mu g/m^3$	0.38	0.35	0.00	1.00	6,523
Yearly NO_2 [$\mu g/m^3$]	37.39	9.14	14.93	61.79	128
Yearly $NO_2 > 40\,\mu g/m^3$	0.38	0.49	0.00	1.00	128
		Post-MC outside MC area			
Traffic (4077 stations)					
Vehicles per hour	446.39	501.91	0.00	4288.60	95,624
Time occupied [%]	6.39	7.06	0.00	95.25	95,624
Pollution (32 stations)					
NO_2 [$\mu g/m^3$]	38.19	18.81	6.59	96.13	903
$NO_2 > 40\,\mu g/m^3$	0.41	0.38	0.00	1.00	903
Yearly NO_2 [$\mu g/m^3$]	35.91	9.12	16.00	59.38	31
Yearly $NO_2 > 40\,\mu g/m^3$	0.26	0.44	0.00	1.00	31

Notes: The table shows descriptive statistics based on weekly station-level data.

of air quality (Auffhammer et al., 2013). For this reason, we use data from the European Climate Assessment Dataset (ECAD), which provides daily measures of several meteorological variables across Europe. We match the pollution measurement data collected by each pollution monitoring station in the city to its closest available weather measurements from the ECAD dataset (represented with a blue cross in Appendix Figure A.1). We consider data on daily mean temperature,

Table 2: Descriptive statistics on weather conditions

	Mean (1)	SD (2)	Min (3)	Max (4)	Obs (5)
Temperature [°C]	15.73	7.53	1.23	30.87	7,657
Precipitation [0.1mm]	10.53	18.15	0.00	158.29	7,657
Cloud cover [okta]	3.40	1.75	0.00	7.71	7,657
Sunshine [h]	8.31	2.97	0.97	13.91	7,657
Pressure [hPa]	1017.18	6.15	997.90	1035.49	7,657
Humidity [%]	57.20	15.52	22.29	92.86	7,657
Wind speed [0.1 m/s]	22.80	10.38	1.71	80.14	7,657
$0° \leq$ Wind direction $< 45°$	0.21	0.22	0.00	1.00	7,657
$45° \leq$ Wind direction $< 90°$	0.15	0.18	0.00	0.86	7,657
$90° \leq$ Wind direction $< 135°$	0.09	0.13	0.00	0.86	7,657
$135° \leq$ Wind direction $< 180°$	0.05	0.10	0.00	0.57	7,657
$180° \leq$ Wind direction $< 225°$	0.12	0.16	0.00	0.86	7,657
$225° \leq$ Wind direction $< 270°$	0.20	0.20	0.00	1.00	7,657
$270° \leq$ Wind direction $< 315°$	0.11	0.15	0.00	1.00	7,657
$315° \leq$ Wind direction $< 360°$	0.07	0.12	0.00	1.00	7,657

Notes: The table shows descriptive statistics on weather conditions at each pollution monitoring station, where weekly weather is obtained from the closest weather monitor.

precipitation, cloud cover, humidity, pressure, wind speed, and wind direction. All these weather variables could influence the complex chemistry of air quality and are commonly used in the literature on air quality. Again, we aggregate all readings to the week-level. To account for the effect of weather on driving, we repeat this matching procedure for linking weather data to traffic monitors. Table 2 shows summary statistics on key meteorological variables. Due to the matching algorithm of weather conditions to air quality observations, the unit of observation in Table 2 is the pollution monitor station level.[14] In our data, temperature is measured in degrees Celsius, precipitation in tenths of millimeters, cloud cover in okta,[15] daily sunshine in hours, pressure in hectopascal, humidity in percentage terms, wind speed in tenths of meters per second and wind direction is indicated by eight equally sized bins.

3.2 Consumption spending data

The final source of data contains information at the credit card transaction-level from a large European bank.[16] While the bulk of our data contains information on

[14] Descriptive statistics of weather data at the traffic monitor level are reported in Appendix Table B.1.

[15] A reading of 0 okta indicates no clouds, and of 8 okta indicates full cloud cover.

[16] For simplicity, we refer to credit card transactions, but these include both credit and debit card transactions. The raw data includes all credit card transactions of consumers living within

brick-and-mortar transactions from January 2015 to June 2019, we also observe online transactions from January 2015 to March 2019. The original data set is unique in that it details the date of each transaction, the zip code of residence of the credit card owner (buyer-zip code) and the zip code of the selling establishment (seller-zip code).[17]

Due to our confidentiality agreement with the bank providing the data, we aggregate brick-and-mortar transaction information at the weekly buyer-seller zip code level from the first week of 2015 to the 26th week of 2019, and until the 10th week of 2019 for online transactions. Figure 2 shows all 122 zip codes in Madrid. Six zip codes belong to the MC area, 49 zip codes to the rest of the city of Madrid, and 67 zip codes are outside the city of Madrid but inside the metropolitan area of Madrid. Those zip codes (even partially) inside the MC area appear in black, zip codes outside the MC area and inside the city appear in orange, and purple zip codes are those outside the city of Madrid but inside the greater metropolitan area. Note that by assuming that all zip codes partially inside the MC area are treated, our estimates may understate the actual impact on consumer behavior if shoppers substitute to establishments within the same zip code.

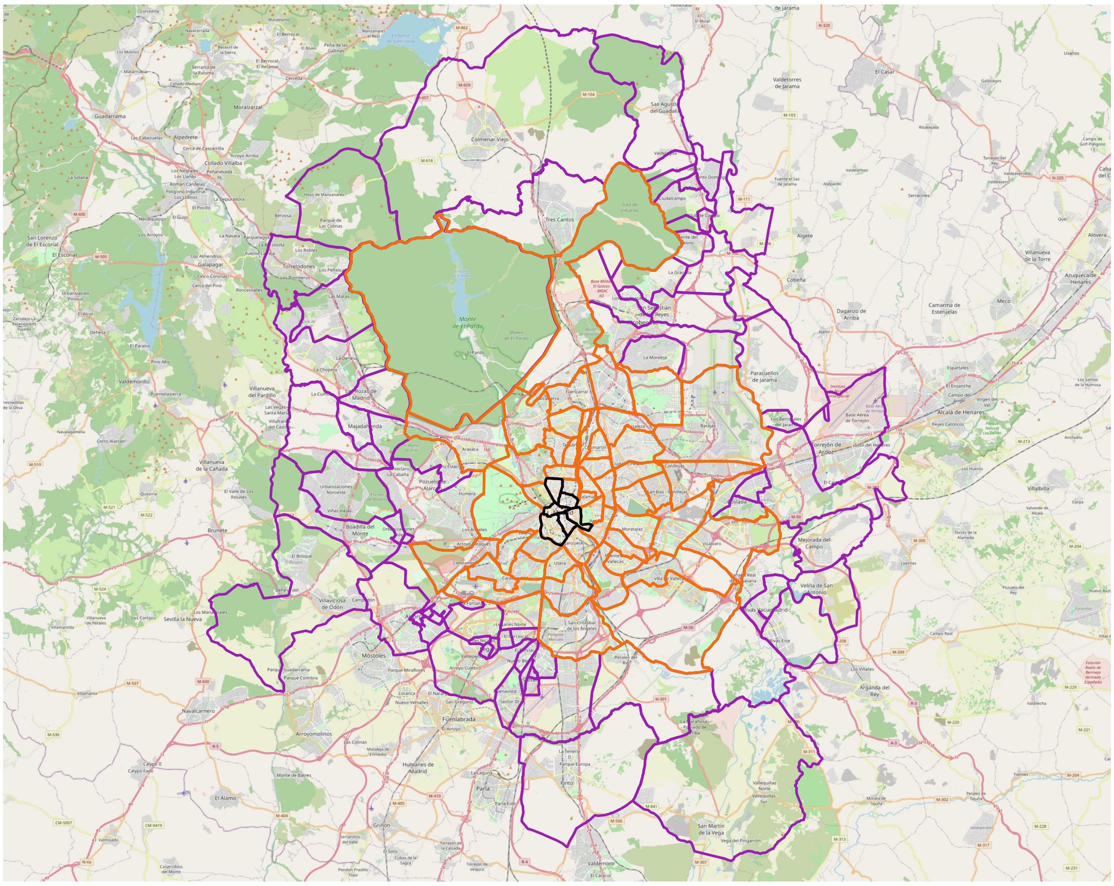
In our data, the average weekly value of brick-and-mortar "trade flows" between zip codes is €2,057 coming from an average of 54 transactions per week and an average value per transaction of €29. Table 3 presents summary statistics for the main variables of our analysis aggregated at the weekly seller-buyer zip codes level. We split summary statistics before and after the implementation of the MC policy for both buyer zip codes outside MC purchasing inside MC, and other zip codes. While "trade flows" of treated pairs (buyer outside MC, seller inside MC) did not change significantly after the implementation of the policy, the value of "trade flows" of untreated pairs increased significantly from €1,953 to €2,423. Interestingly, transactions increased after the implementation of MC in both groups of zip code pairs, but the average transaction value decreased from €41 to €30 in treated pairs and increased from €28 to €33 in untreated pairs. Our empirical analysis will aim to study changes in these differences over time.

A unique feature of our data is that we are able to separate transactions into brick-and-mortar and online transactions until the tenth week of 2019. This is an

the metropolitan area of Madrid made in establishments within the metropolitan area of Madrid with a credit card of the bank providing the data. Approximately, the data covers 15% of all transactions in the area, and can be considered as a representative sample of the credit card purchasing behavior in the overall population of the area. Galdon-Sanchez et al. (2020) provide a detailed description of the database.

[17]A zip code in our context is comparable to a 5-digit zip code in the US.

Figure 2: Map of zones and postal codes



Notes: The black lines mark zip codes subject to the regulations of Madrid Central. The orange lines mark unregulated zip codes inside the city of Madrid. The purple lines mark unregulated zip codes outside the city of Madrid but in the greater metropolitan area. Source: OpenStreetMap.

important feature because it allows us to test the transportation cost mechanism given that, due to the nature of the policy, transportation costs increase for brick-and-mortar transactions, but they do not for online transactions. Introducing this additional level of heterogeneity enriches the substitution patterns between zip codes within and outside the MC area. On the one hand, when consumers' demand for brick-and-mortar transactions is elastic, higher transportation costs will prompt consumers residing outside the MC area to substitute their former purchases in the MC area for purchases in other areas. On the other hand, those consumers with inelastic demand for products from specific treated zip codes may substitute to online transactions. This second scenario is more likely when the retailer sells a differentiated good and, therefore, it is costly to find a suitable brick-and-mortar transaction substitute outside the MC area. The total value of online transactions is on average €132, coming from three online transactions.

Table 3: Descriptive statistics on sales

	Mean (1)	SD (2)	Min (3)	Max (4)	Obs (5)
	Pre-MC buyer outside, seller inside				
Value	3019.94	4675.65	0.00	80,155.81	142,680
Transactions	72.99	118.27	0	2062	142,680
Transaction value	40.61	42.85	0.50	2295.72	142,680
	Post-MC buyer outside, seller inside				
Value	3042.44	4579.19	0.00	70,369.95	20,382
Transactions	97.44	139.57	0	1485	20,382
Transaction value	29.97	15.57	1.00	380.28	20,382
	Pre-MC other pairs				
Value	1953.04	9731.32	0.00	606,386.90	2,908,540
Transactions	51.01	268.99	0	14,454	2,908,540
Transactions value	27.61	38.41	0.13	9227.48	2,908,540
	Post-MC other pairs				
Value	2423.48	11,883.77	0.00	556,122.80	401,704
Transactions	69.09	370.64	0	15,342	401,704
Transaction value	32.80	15.21	0.58	706.09	401,704

Notes: The table shows descriptive statistics on sales at the weekly seller-buyer level.

Additionally, 23% and 71% of weekly seller-buyer zip codes observations are zero for brick-and-mortar and online transactions, respectively.

Table 4 presents basic summary statistics related to selling and purchasing patterns across zip codes in Madrid until March 2019. The top half of Table 4 details summary statistics at the seller-zip code level. We can see how the share of revenue coming from online sales changes across zip codes in different areas. While zip codes in the MC area produce 85.6% of their revenue from brick-and-mortar sales, the percentage increases for zip codes in the rest of the city of Madrid and outside the city (90% and 95%, respectively). Moreover, the mean value of brick-and-mortar and online transactions also changes across zip codes. Finally, the last two rows in the top half of the table show the share of sales that establishments in the MC area are selling to different areas of Madrid. Not surprisingly, we see that brick-and-mortar sales are tilted towards consumers in the local zip code. Zip codes in the MC area sell, on average, 5.62% of their sales to each of the zip codes in the MC area but only 0.21% to each of the zip codes outside the city of Madrid. Geographical proximity also matters for online sales (as documented by Blum and Goldfarb, 2006). On average, 1.84% of the online sales from zip codes in the MC area go to each of the six zip codes in this area, 1.34% go to each of

TABLE 4: Descriptive statistics on consumption

	MC Area (1)	Madrid City (2)	Outside Madrid City (3)
Number of zip codes	6	50	70
Seller-zip code statistics			
Share of revenue coming from B&M sales	85.6%	90%	95%
Mean value of B&M sales	38.28	36.75	41.1
Mean value of online sales	63.2	44.58	54.79
Mean share of B&M sales by zip codes in Madrid Central to each of the zip codes in MC, Madrid City, or outside Madrid City	5.62%	1.12%	0.21%
Mean share of online sales by zip codes in Madrid Central to each of the zip codes in MC, Madrid City, or outside Madrid City	1.84%	1.34%	0.40%
Buyer-zip code statistics			
Share of B&M purchases in MC	45.2%	8.9%	4.3%
Share of online purchases in MC	20.3%	18.70%	14.80%
Share of B&M purchases in local zip code	27%	28.50%	38.70%
Share of online purchases in local zip code	13.10%	15.10%	14.3%

Notes: The table shows descriptive statistics on selling and purchasing patterns at the weekly level for brick-and-mortar (B&M) and online transactions.

the 49 zip codes in Madrid city and only 0.4% to each of the 67 zip codes outside of the city of Madrid.

The bottom half of Table 4 reports statistics on consumer behavior by buyer-seller-zip code dyad until March 2019. Consumers living in the MC area carry 45.2% of their brick-and-mortar purchases and 20.3% of their online purchases in establishments inside their area. These shares decrease monotonically with the distance to MC. Consumers in other zip codes of the city of Madrid make, on average, 8.9% of their brick-and-mortar purchases and 18.7% of their online purchases in establishments within the MC area. For consumers living outside the city, these numbers decrease to 4.3% of brick-and-mortar purchases and 14.8% of online purchases. The last two rows show how much consumers spend within their local zip code depending on where they live in Madrid. As the share of brick-and-mortar sales that consumers make in their local zip code is concerned, we see that consumers outside the city tend to spend more (38.7% of their total brick-and-mortar expenditures) than consumers elsewhere. By contrast, we do not see large differences across areas in the propensity to buy online in the local zip code (13.1% for consumers in MC, 15.1% for consumers in the city, and 14.3% for consumers outside the city).

4 The effect of Madrid Central on car traffic and air quality

The main goal of the regulation of MC is to reduce traffic in the city center of Madrid and thereby lower air pollution. In this section, we study whether the policy achieved that goal. MC focuses on the reduction of NO_2, a pollutant mainly emitted by vehicles, as the city of Madrid repeatedly violated NO_2 limit values defined by European Union environmental regulation. After defining our empirical strategy, we show our results of the impact of MC on traffic and air pollution.

4.1 Empirical strategy

We estimate the effect of MC on traffic or NO_2 levels using the following regression equation.

$$Y_{swy} = \beta MC_{swy} + \delta X'_{swy} + \mu_{sw} + \tau_{wy} + \epsilon_{swy} \tag{1}$$

The dependent variable Y_{swy} stands for the traffic or pollution outcome of interest at the traffic or air quality monitor station s in week w of year y. It is important to note that the traffic and air quality monitors are not identical. The variable MC_{swy} is a dummy that takes value one if station s is inside the MC area in a year-week in which MC is in effect. The vector X'_{swy} includes controls for meteorological conditions at the location of station s, week w, and year y. Therefore, the coefficient δ captures the effect of weather on air pollution levels.[18] For example, these would control for the case that the introduction of MC coincided with the wind blowing from a direction that induces lower pollution levels in the MC area. Moreover, we include station-week fixed effects μ_{sw} to control for season-specific patterns at each monitoring station. This set of fixed effects controls for instance for the case that during the Christmas season many shoppers go to the city center, increasing traffic and pollution levels. The variable τ_{wy} controls non-parametrically for time trends and year-week-specific shocks. This variable controls, for example, for the celebration of specific events attracting many visitors to the city and affecting pollution levels. The error term ϵ_{swy} is potentially serially correlated, so we cluster standard errors at the station level. By using this specification, we aim to consistently estimate the effect of MC on air pollution, captured

[18] This includes second order polynomials of temperature, precipitation, cloud cover, humidity, pressure and wind speed, as well as wind direction indicators interacted with station indicators.

by β, while controlling for possible confounding factors. To account for the fact that fines were only levied after March 2019, we will include in Equation (1) an additional indicator that takes values 1 if station s is inside the MC area and the year-week is after the 12th week of 2019, and 0 otherwise.

While the use and structure of our difference-in-differences methodology is intuitive, it is important to account for the fact that treated and untreated stations are not completely independent because of diverted traffic from the MC area to other areas and the associated pollution. We must also note that our estimation strategy requires common trends in treated and untreated stations once we account for all control variables. This could fail, for instance, if people living in the MC area were substituting their old cars for electric vehicles at a faster pace than people in other areas of Madrid were. To account for this, we can allow for station-specific trends. Our estimates could still be compromised if there were other policies introduced at the same time as MC, affecting traffic or pollution levels in specific areas of the city. If, for instance, a metro line covering the city center opens at the same time as the introduction of MC, we could wrongly attribute the metro's positive effect on air quality to MC. We are not aware of any policy change or intervention of this type during the time span of our data set.[19]

Figure 3 displays time series of average NO_2, vehicles per hour, and the time percentage a road segment is occupied inside and outside the MC area. For visual clarity, we remove seasonality at the station level and common time trends. The introduction of MC is marked by the dashed red lines.

Sub-Figure 3a plots average NO_2, where the time series inside MC comes from a single station. We can see average NO_2 drops substantially after the introduction of the driving restrictions. For the two measures of traffic in Sub-Figures 3b and 3c, one can also observe a substantial drop. However, the previous decrease in traffic during 2018 could potentially point to differential trends and requires further discussion.

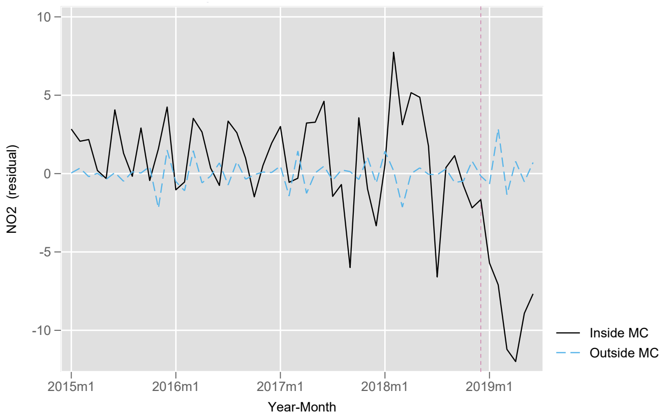
In 2018, downtown Madrid faced a wave of construction works.[20] Almost all major roads inside the area to become Madrid Central were at some point subject to limitations and temporary closures during 2018. This construction campaign led to substantial changes in traffic in the center of Madrid. As most of 2018

[19] In January 2019, the City Council of Madrid reduced the speed limit on highway M-30 in order to decrease pollution levels. As this route does not cross the MC area, if anything, we would expect the policy to decrease pollution levels in the control group.

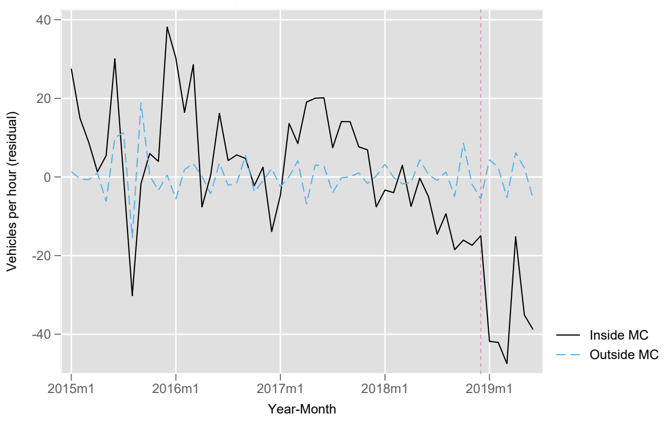
[20] See for example https://www.20minutos.es/noticia/3295933/0/obras-centro-madrid/ for an overview.

Figure 3: Pollution and traffic inside and outside of Madrid Central

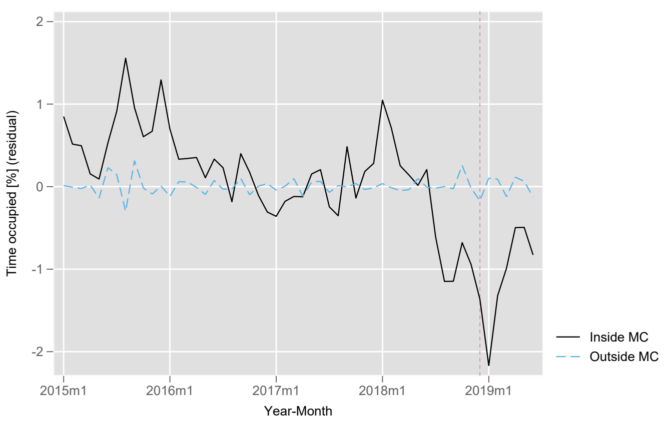
(a) Average NO_2 in µg/m^3



(b) Vehicles per hour



(c) Time occupied [%]



Notes: All plots show weekly averages for the period January 2015-June 2019 after removing common trends across stations and seasonality.

Table 5: Effects on traffic levels

	Vehicles per hour (1)	Time occupied [%] (2)	Log Vehicles per hour (3)	Log Time occupied (4)
Madrid Central	−56.51***	−2.173**	−0.161***	−0.210***
	(13.88)	(0.947)	(0.0272)	(0.0515)
Madrid Central Post March 2019	6.005	1.354***	0.0357**	0.104***
	(5.061)	(0.514)	(0.0139)	(0.0382)
Location-Week FE	Yes	Yes	Yes	Yes
Year-Week FE	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes
Mean dep. var.	456.1	6.567	5.646	1.493
N×T	646,819	646,493	646,629	642,111
N	3966	3966	3966	3945

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Standard errors are clustered at the station level. The variable Madrid Central takes value 1 when a station is located within the MC area and the MC regulations are in place, and 0 otherwise. The variable Madrid Central Post March 2019 takes value 1 in the same case and when the week is after March 2019. The weather controls are second order polynomials of temperature, precipitation, cloud cover, humidity, pressure and wind speed, as well as wind direction indicators interacted with station indicators.

belongs to the pre-treatment time, our estimates of traffic in the city are likely underestimated and represent a lower bound of the real effect of MC.

4.2 Results

Table 5 presents the results of estimating Equation (1) for the two measures of traffic, in levels and logs, with standard errors clustered at the station level.[21] We find large effects of MC on traffic. The average number of cars dropped by 56.5 (column 1), or 16.1 percent (column 3). MC reduced the frequency of road segment usage by cars by 2.2 percentage points (column 2), or 21.0 percent (column 4). Once penalties were introduced at the end of March 2019, the effect on traffic was partially reversed. For example, the time a road segment was occupied now was only 10.6% smaller than its level prior to Madrid Central. This could be explained by a move toward a new equilibrium in which drivers with eligible vehicles have learned about emptier streets in downtown Madrid.

Because those that cannot enter the restricted area may park in areas close by or not drive to the center at all, MC might generate spatial spillover effects (either

[21]Standard errors are smaller when clustering at the zip code level, likely due to traffic moving around a road closed for construction work. Estimates are reported in Appendix Table C.1.

positive or negative) in traffic levels to nearby areas. In fact, our initial regression specification may be overestimating the decrease in traffic in the restricted area. To account for the spillover, we include a dummy variable in Equation (1) that takes value 1 if station s is inside a 1.5 km buffer around the MC area in a year-week in which MC is enforced, and 0 otherwise. Appendix Table C.2 shows that the net spillovers are positive, i.e. that traffic is also reduced in streets close to the regulated area. As expected, the magnitude of the reduction is smaller than inside the MC area. One can also see that four months after the implementation of MC this clear evidence of positive spillovers has vanished.

Table 6 presents the results on air quality. We cluster the standard errors in all specifications at the air quality monitor level. In column 1, we use the log of the average weekly level of NO_2 as the dependent variable. Our findings suggest a decrease of 18.6 percent in NO_2 in the restricted area due to the introduction of MC, with a further drop to as much as 41.4% once illegal entry was penalized.

The main source of NO_2 is combustion by vehicles and power plants.[22] As large industrial installations do not play a role for downtown Madrid, we expect that the reduction in NO_2 is largely due to the observed adjustments in traffic.

Spillovers in air quality may occur because of air transport. A metastudy by the U.S. Environmental Protection Agency (Liu et al., 2019) estimates decay rates of traffic pollution away from its source. NO_2 exhibits a significant gradient, even in the downwind area. Their results suggest, for example, that 300 meters away from a road NO_2 concentration falls by 21%. This means that air quality in areas of close proximity to MC may also have benefited from the regulation.

Defining the three closest stations inside the 1.5 km buffer around the MC area as its immediately adjacent area, the results in column 2 show that (i) the estimated reduction in pollution levels in the MC area remains unchanged, and (ii) there is no evidence of net spillovers to adjacent areas. We repeat the same exercise in column 3 considering spillovers to any station within the city of Madrid, but we find no evidence of spillovers neither towards adjacent areas nor to areas in the rest of the city. These estimates cannot be compared to the results on traffic, as traffic outside the city of Madrid is unobserved.

In columns 4 to 6, we show results of running the same specification with a different dependent variable, the share of days in a week in which NO_2 levels exceed $40\,\mu g/m^3$. Our findings here are consistent with those reported in columns 1 to 3, suggesting a decrease of 16.9 to as much as 33.6 percentage points in the number of days per week in which NO_2 levels exceed $40\,\mu g/m^3$. This represents a

[22]See for example https://www3.epa.gov/region1/airquality/nox.html.

Table 6: Effects on NO_2 levels

	Log NO_2			$NO_2 > 40$		
	(1)	(2)	(3)	(4)	(5)	(6)
Madrid Central	−0.186***	−0.189***	−0.193***	−0.169***	−0.171***	−0.180***
	(0.016)	(0.017)	(0.029)	(0.013)	(0.014)	(0.020)
Madrid Central Post March 2019	−0.231***	−0.235***	−0.266***	−0.167***	−0.166***	−0.188***
	(0.019)	(0.020)	(0.038)	(0.019)	(0.020)	(0.023)
Surroundings		−0.030	−0.033		−0.024	−0.033
		(0.036)	(0.043)		(0.027)	(0.030)
Surroundings Post March 2019		−0.040	−0.071		0.004	−0.019
		(0.056)	(0.064)		(0.044)	(0.045)
City of Madrid			−0.006			−0.012
			(0.034)			(0.024)
City of Madrid Post March 2019			−0.042			−0.030
			(0.040)			(0.026)
Station-Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes	Yes
Mean dep. var.	3.521	3.521	3.521	0.392	0.392	0.392
N×T	7657	7657	7657	7657	7657	7657
N	33	33	33	33	33	33

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Standard errors are clustered at the station level. The variables take value 1 when a station is located in the indicated area and the MC regulations are in place, and 0 otherwise. The variables referring to Post March 2019 takes value 1 in the same case and when the week is after March 2019. The weather controls are second order polynomials of temperature, precipitation, cloud cover, humidity, pressure and wind speed, as well as wind direction indicators interacted with station indicators.

significant reduction relative to the average observed inside MC before the policy, which was 65%.

Appendix Table C.3 allows to draw conclusions on within-day dynamics of air pollution. The effect of MC on the daily maximum and the daily 8-hour maximum of NO_2 is significant, with reductions of 15.8% and 11.2%, respectively, with further reductions once fines were levied. This shows that the incidence of extreme-pollution events was reduced substantially by MC.

4.3 Robustness checks

While aggregating traffic and pollution measures yields better comparability to the analysis of consumption behavior, it introduces measurement error. Therefore, we repeat the analysis at the daily monitor level and also include day fixed effects. The results are very similar and reported in Appendix Tables C.4 and C.5.

Our main analysis controls for weather using polynomials. The regression results when we control instead for weather by interacting ten by ten by ten indicators of temperature, precipitation, and wind speed deciles are very similar and can be found in Appendix Tables C.6 and C.7.

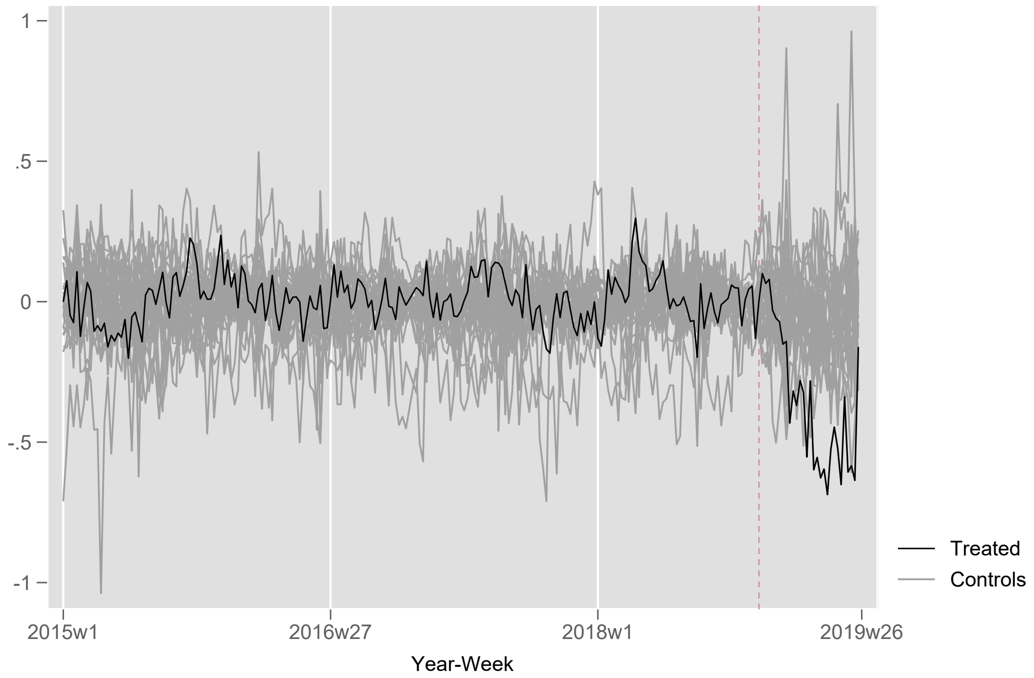
Public holidays may affect traffic patterns across Madrid differently. To account for this, we include in the estimation holiday controls and allow them to vary for each station.[23] As Appendix Tables C.8 and C.9 demonstrate, this barely changes the estimates. Our results on air quality also appear to remain unchanged both qualitatively and quantitatively when including station-specific trends (Appendix Table C.10).

Finally, as only a single station is treated and the number of clusters is relatively small (33), we also implement the Synthetic Control Method to estimate the impact of MC on air quality in downtown Madrid (Abadie et al., 2010). The station located inside the MC area is matched to a number of monitors outside the MC area based on pre-treatment data of air quality. Each control monitor receives a certain weight, such that the weighted mean of the control monitors' readings predicts air quality at the treated monitor. The algorithm chooses weights to minimize the mean squared error of these predictions. While one could try to find optimal weights by predicting every single observation of air quality at the treated monitor prior to intervention, we only choose a subset of NO_2 readings to be matched. From the beginning of 2015 to mid-2018, i.e. the 25th week of 2018, we only consider air quality from every 20th week to avoid overfitting. After that, we consider all readings until the 47th week of 2018. Treatment begins in the 49th week of 2018. In addition, we also match on the pre-treatment average of NO_2. We do not make use of weather controls as additional matching variables since, by construction, most stations face almost exactly the same weather conditions. Before running the algorithm, we deseasonalize each station's data. The matched stations provide good predictions of pre-treatment NO_2 concentrations at the station inside the MC area with an R-squared of 0.87.

Figure 4 shows the effect on the treated station (in black). It seems that, at the beginning, MC was not yet effective. However, after some weeks, it decreased NO_2 levels by close to 50 percent. We cannot calculate standard errors, but repeat the analysis with a placebo treatment for each other monitor (in gray). Comparing the results from these stations, we see that the 50% drop can be interpreted

[23] Retrieved from https://pypi.org/project/holidays/.

Figure 4: Synthetic control method for pollution levels



Notes: The figure plots synthetic control estimates. The black line marks the treated station, the gray lines the controls. All lines plot the difference between an actual measurement and a prediction based on controls stations. The vertical red line indicates the introduction of Madrid Central.

as an unusually large deviation. Abadie et al. (2010) suggest that an effect is significant if the estimated effect of the treated unit is unusually large compared to the distribution of placebo estimates. They propose that one should not simply compare mean squared prediction errors of treated and placebo units in the post-treatment period, but scale these errors by the respective mean squared prediction errors in the pre-treatment period. In our case, we find that the ratio of mean squared prediction errors of the treated air quality station is larger than the ratios of all 32 control stations.

5 The effect of Madrid Central on consumption spending

The results in Section 4 indicate that MC achieved its goal of reducing car traffic and pollution levels in the city center of Madrid. However, the correction of this negative externality may come at the cost of changing citizens' habits and market outcomes. One of the most salient and controversial dimensions of these policies is the possible impact that MC may have had on consumption and spending behavior. An increase in the cost of transportation to the MC area can potentially discourage consumption in that area. In this section, we empirically examine whether MC affected consumer behavior, and if so, how. Understanding the costs of pollution-reducing policies is as important as evaluating their benefits. Therefore, the results of this section may help policy makers derive conclusions for the introduction of similar policies in the future.

Our theoretical framework yields predictions of the impact of an increase in transportation costs (actual transportation costs or disutility through inconvenience) for consumers living outside the MC area when they make purchases of goods and services from businesses within the MC area. In our context, changes in transportation costs induced by MC should not directly affect: (i) purchases of residents from the MC area in businesses within the MC area; (ii) purchases of residents outside the MC area in businesses outside the MC area, as the regulation only restricts traffic inside the MC area; and (iii) purchases of residents from the MC area in businesses outside the MC area. In other words, we are able to clearly define which "trade flows" are directly affected by the policy and which are unaffected. Therefore, the predictions from our theoretical framework and our empirical analysis allow us to identify the impact of the increase in transportation costs for those affected, whilst controlling for demand shocks and supply shocks at different zip codes.

Following this intuition, we aggregate transactions at the week level for each combination of seller-zip code and buyer-zip code dyads available in the data. The resulting data set contains weekly information on how much consumers of each zip code are buying from sellers of each zip code in Madrid.[24]

5.1 Theoretical framework and identification strategy

We build our identification strategy using a theoretical framework based on a standard gravity model and the seminal work of Anderson (1979), Eaton and Kortum (2002) and Baier and Bergstrand (2007). Assume a city with N zip codes, and each zip code has buyers and sellers. For simplicity, we consider buyers

[24] This data structure is comparable to that found in the international trade literature for the estimation of gravity equations (Head and Mayer, 2014; Atalay et al., 2019). Analogously to the trade literature, our data allows us to study how "trade flows" between different geographical areas change when transportation costs change exogenously.

indexed by their zip code $i = 1, \ldots, N$ and sellers indexed by their zip code $j = 1, \ldots, N$. The sellers in each zip code sell an item differentiated from all items sold in other zip codes. Buyers may choose to buy items from any zip code, and sellers can sell to buyers from any zip code. While this is effectively a static model, we allow for multiple periods indexed according to their week of the year $w = 1, \ldots, W$, and their year $y = 1, \ldots, Y$.

Consider then a representative consumer model with a CES demand function in which the buyer residing in zip code i, in week w of year y, has to decide how much to buy from each of the seller zip codes j (Q_{ijwy}). There is a seasonal (weekly) taste-specific shock θ_{ijw} at the level of the buyer-seller-week. A seller of zip code j cannot price discriminate across different buyers and therefore sets a price P_{jwy} common to all buyers. Moreover, buyers incur iceberg transportation cost τ_{ijwy}. Because we want to study the impact of the introduction of MC on spending flows between zip codes, we allow transportation costs to vary at the buyer-seller-week-year level. In our case, we hypothesize that the introduction of MC will affect the purchases in zip codes inside the MC area from buyers in zip codes outside of MC area. Therefore, the objective function U_{iwy} is the following.

$$U_{iwy} = \left(\int \theta_{ijw} Q_{ijwy}^{\frac{\sigma-1}{\sigma}} dj \right)^{\frac{\sigma}{\sigma-1}} - \int \left(\tau_{ijwy} P_{jwy} \right) Q_{ijwy} dj$$

Each consumer maximizes her consumer surplus with respect to Q_{ijwy} taking preferences, prices and other parameters as given.

Let $\widetilde{P}_{iwy} = \left(\int \theta_{ijw} (\tau_{ijwy} P_{jwy})^{1-\sigma} dj \right)^{\frac{1}{1-\sigma}}$ be the price index of buyer i, in week w of year y. Let also $\widetilde{Q}_{iwy} = \left(\int \theta_{ijw} Q_{ijwy}^{\frac{\sigma-1}{\sigma}} dj \right)^{\frac{\sigma}{\sigma-1}}$ be the total amount consumed by buyer i, in week w of year y. Then, the total value of consumption by buyers residing in zip code i, in establishments of sellers in zip code j, in week w of year y will be equal to

$$P_{jwy} Q_{ijwy} = (\widetilde{P}_{iwy}^{\sigma} \widetilde{Q}_{iwy})(P_{jwy}^{1-\sigma})(\theta_{ijw}^{\sigma-1})(\tau_{ijwy}^{-\sigma})$$

Here we can see how an increase in transportation costs τ_{ijwy}, like the one induced by the introduction of MC, will reduce consumption levels.[25] Moreover,

[25] The increase in transportation costs induced by the introduction of MC will have a direct impact on the level of purchases from buyer-zip codes outside the MC area in establishments inside the MC area. In turn, if the spending reduction in the MC area has spillovers in consumption levels in other zip codes, these should be controlled for by the fixed effects structure. We will not be able to separate this indirect effect of the introduction of MC from aggregate shocks at the buyer-zip code level. However, note that this impact should be economically small

this expression can be mapped one-to-one (using logs) to the following equation that we will actually estimate with our data,

$$Y_{ijwy} = \alpha_{iwy} + \gamma_{jwy} + \delta_{ijw} + \beta Treatment_{ijwy} + u_{ijwy} \tag{2}$$

where Y_{ijwy} measures (log) expenditures of residents in zip code i in establishments in zip code j during week w of year y. The variable $Treatment_{ijwy}$ is a dummy variable that takes value 1 if i is a buyer-zip code outside the MC area, j is a seller-zip code inside the MC area, and we are in a week-year in which the MC regulations are in effect, and 0 otherwise. Our empirical specifications in the following sections will also include another dummy similarly defined for weeks after March 2019. Note these dummies are aimed to capture the impact of increases in transportation cost between a zip code pair triggered by the introduction of MC. In this specification, β is the coefficient of interest as it measures the effect of MC on purchases of buyers from outside the MC area in establishments inside the MC area once the policy is in effect. Additionally, α_{iwy} is the buyer-by-week fixed effect, and γ_{jwy} is the seller-by-week fixed effect.[26] The variable δ_{ijw} is the buyer-by-seller fixed effect specific for each week of the year. We allow this dyad-specific fixed effect to vary by the week of the year to account for seasonality patterns (e.g. during Christmas time people living in the outskirts of the city may disproportionately increase their shopping in the city center). Finally, u_{ijwy} is the error term.

As a result, through specification (2) we aim to identify the effect of MC on spending levels from buyers living in zip codes outside the MC area in establishments inside the MC area, both relative to the shopping of these same consumers in other areas of the city and relative to the shopping in downtown Madrid of consumers living within the MC area.

The coefficient of interest, β, identifies the partial equilibrium effect of the increased transportation costs due to MC. Additionally, these cost changes also have a general equilibrium effect as a result of demand substitution. In the case of CES-demand, this is captured by changes in the price index $\widetilde{P}_{iwy}$ and, hence, they affect consumption spending of buyers located in zip codes outside of the MC area

if the number of zip codes is large enough. We have 122 zip codes, which should make our case comparable to the usual International Trade framework modeling trade across countries.

[26]The buyer-zip code-week fixed effect α_{iwy} and the seller-zip code-week fixed effect γ_{jwy} would correspond to the importer-period and exporter-period fixed effects in trade models. The parameter α_{iwy} controls for changes over time in the average level of expenditures of people living in zip code i. The parameter γ_{jwy} controls for changes in the attractiveness of shopping in zip-codes inside the MC area.

in all seller-zip codes, both inside and outside of the MC area (Larch and Yotov, 2016; Piermartini and Yotov, 2016).[27] In Equation (2), these changes in the price index $\widetilde{P}_{iwy}$ are captured by the set of buyer-by-week fixed effects α_{iwy}.[28]

As discussed as well in Section 4.1, the validity of our triple difference methodology relies on the assumption of parallel trends between treated and control groups. We investigate the validity of this assumption by running specification (2) without our triple interaction dummies *Treatment* and *Treatment Post March 2019*, taking the weekly average error term across buyer-seller zip codes pairs, and plotting them over time. Figure 5 shows the result of plotting average error terms for each group from total weekly spending (top Figure 5a) and weekly number of transactions (bottom Figure 5b). It is straightforward to see parallel trends between treated pairs (buyer outside MC, seller inside MC) and other pairs in both figures prior to December 2018. It is also noticeable the drop in total value and number of transactions after the implementation of MC in December 2019.

5.2 Main Results

Following the empirical strategy described in the previous section, we proceed next with our "gravity-like" methodology. Because the outcome variables in this section are measured in logs and the spending flows between two zip codes in a given week can be zero, we add the value one to the dependent variable of interest throughout this section.[29]

We estimate β from specification (2) and show results of the triple difference estimation in Table 7. We cluster the standard errors in all specifications at the buyer-seller zip code pair level. In column 1, we use total transaction revenue as the dependent variable and find a statistically significant decrease of 20.6 percent in brick-and-mortar spending in the MC area by consumers not living in the MC

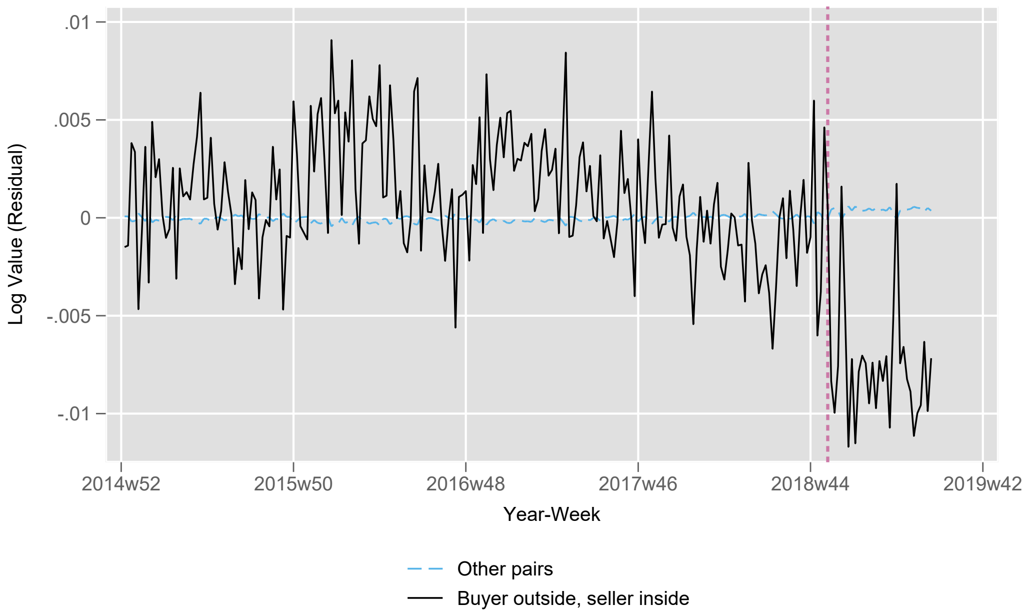
[27] A similar mapping exists for a logistic specification of demand to our estimates (e.g. Berry, 1994).

[28] Arguably, in addition to the increase in transportation for consumers living outside of the MC area, the traffic ban also changed the attractiveness of the MC area (e.g. because walking in that area is nicer after the introduction of MC). In our model, that would imply that θ_{ijw} increases for all buyer-zip codes i when buying in zip codes j that are in the MC area after the regulation came into effect. Because this is a general effect for all buyer-zipcodes, its impact would be fully captured by the seller-by-week fixed effect γ_{jwy}. Our baseline specification will not allow us to separate this potential change in the attractiveness of seller-zip codes in the MC area from other supply shocks taking place simultaneously in those places that are also captured by the seller-by-week fixed effect.

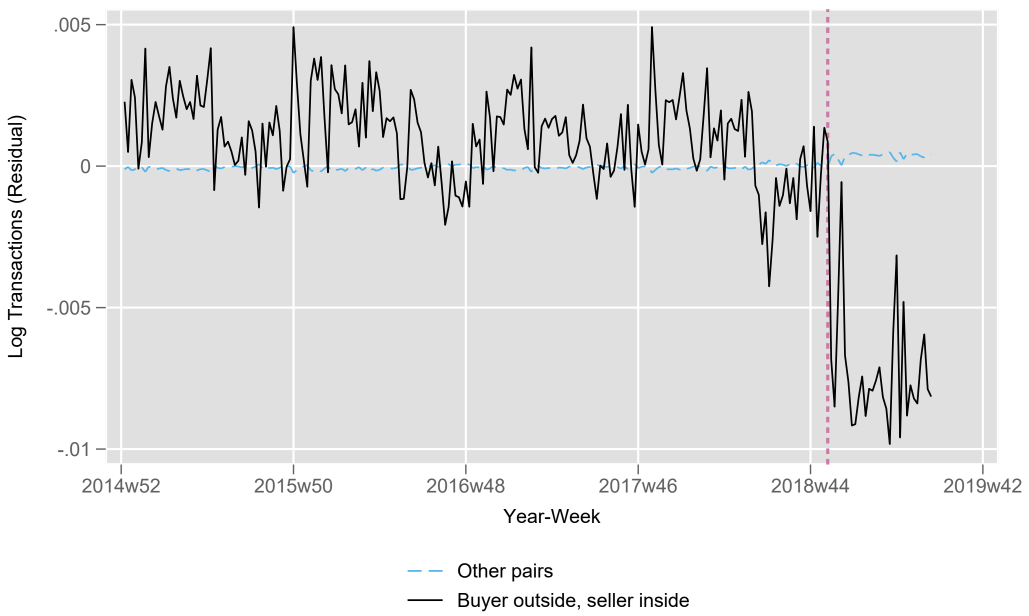
[29] Up to 14.1% of the dyad-week flows are zero in our sample. This is substantially lower than in usual setups of country trade flows where there are around 50% of zeros (Helpman et al., 2008).

Figure 5: Consumption by zip code-pairs

(A) Value of spending at the zip code-pair level



(B) Number of transactions at the zip code-pair level



Notes: All plots show weekly averages for the period January 2015-June 2019 after removing week-year effects for each buyer and each seller zip code as well as buyer-seller pair specific seasonality.

Table 7: Main Results

	(1) Value	(2) Transactions	(3) Transaction Value	(4) Merchants	(5) Cards
Treatment	-0.206***	-0.193***	-0.0125	0.0113	0.00302
	(0.0459)	(0.0342)	(0.0427)	(0.0108)	(0.0116)
Treatment Post March 2019	0.00680	-0.000607	0.00741	-0.0269**	-0.0296**
	(0.0190)	(0.0145)	(0.0131)	(0.0115)	(0.0121)
Buyer-week-year FE	Yes	Yes	Yes	Yes	Yes
Seller-week-year FE	Yes	Yes	Yes	Yes	Yes
Buyer-seller-week FE	Yes	Yes	Yes		
Buyer-seller FE				Yes	Yes
Observations	3458422	3458422	3458422	548582	548582

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Standard errors are clustered at the buyer-seller zip code pair level. The dependent variable is in logs at the seller-zip code by buyer-zip code level in a given week. The variable Treatment takes value 1 when (1) a seller-zip code is within the MC area and the MC regulations are in place, and (2) the buyer-zip code is outside the MC area, and 0 otherwise. The variable Treatment Post March 2019 takes value 1 when the dummy Treatment takes value 1 and the week is after March 2019.

area. Given the mean of "trade flows" reported in Table 4 between treated buyer-seller zip codes pairs, a 20% decrease implies a weekly loss of €600 per zip code pair. A quick back-of-the-envelope calculation accounting for the 116 zip codes outside the MC area in our data would sum up to €70,000 weekly loss and €3.6 million annually. After accounting for the fact that our bank data provider has 15% market share, the overall loss could come up to €24 million. This amount is a rough estimate of the value of the deadweight loss created by the pollution externality and corrected by the MC policy.

Additionally, column 2 examines the impact of MC on the number of brick-and-mortar transactions and shows that MC decreases brick-and-mortar transactions by 19.3 percent. Column 3 shows there is no statistical change due to the introduction of MC on average transaction values. Finally, columns 4 and 5 take advantage of the fact that we observe the number of merchants and credit cards used daily from a buyer zip code in a seller zip code from October 1st 2018 to June 30th 2019. The specifications in columns 4 and 5 contain buyer-seller zip codes pair fixed effects (as opposed to buyer-seller-week specific fixed effects). Our results show a decrease of around 3 percent after March 2019 in both daily merchants and daily cards used.

Our data also details online transactions until March 2019. Table 8 shows results of running specification (2) with weekly online spending, number of online

Table 8: Impact of MC on Online Spending

	(1) Value	(2) Transactions	(3) Transaction Value
Treatment	0.121**	0.094**	0.027
	(0.061)	(0.044)	(0.046)
Buyer-week-year FE	Yes	Yes	Yes
Seller-week-year FE	Yes	Yes	Yes
Buyer-seller-week FE	Yes	Yes	Yes
Observations	3,460,968	3,460,968	3,460,968

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Standard errors are clustered at the buyer-seller zip code pair level. The dependent variable is log of revenue, log of number of transactions, and log transaction value for online transactions at the seller-zip code by buyer-zip code level in a given week. The variable Treatment takes the value one when (1) a seller-zip code is within the MC area and the MC regulations are in place, and (2) the buyer-zip code is outside the MC area, and 0 otherwise.

transactions, and average online transaction value as dependent variables. We cluster the standard errors in all specifications at the buyer-seller zip code pair level. We find that MC increased online spending of consumers living outside the MC area by 12.1 percent and the number of transactions by 9.4 percent, with no statistically significant change in the mean value of online transactions. These results suggest that, upon the increase in transaction costs due to the implementation of MC, consumers in zip codes outside the MC area switched part of their consumption spending from brick-and-mortar to online transactions in those zip codes within the MC area. Additionally, Appendix Table D.1 shows results of regressions of the share of online revenue and the share of online transactions per buyer-seller zip codes dyad on our *Treatment* and we find results consistent with those in Table 8, as well as no statistical change in the relative size of brick-and-mortar to online transaction values.

It is important to emphasize that estimates in Table 7 correspond to the partial equilibrium impact of MC, as explained in Section 5.1. This means that the changes in consumption of affected consumers shopping inside the MC area are expressed relative to their total consumption. In a general equilibrium context, this total consumption can also adjust because of substitution effects. For instance, the 20 percent decrease in brick-and-mortar spending in the MC area by consumers living outside the MC area is relative to the total consumption of these consumers, which might change in general equilibrium. If substitution effects are only small, our estimates should also be close to the total effects. If they are large, the total effect would be smaller than 20 percent. Because only six out of 122 zip codes were directly affected by MC, we anticipate that general equilibrium responses do not play a large role. This clarification does not affect the result that aggregate spending in the MC area by affected consumers is unchanged, as we find no effect, but it could matter when we qualify the observed decrease in brick-and-mortar spending and the increase in online spending.

5.3 Result Heterogeneity and Robustness Checks

In this section, we explore result heterogeneity and robustness of the main results provided in Table 7. An interesting departure from specification (2) is one that studies whether higher income zip codes were more or less affected by MC. For this purpose, we interact our dummy of interest, $Treatment_{ijwy}$, with a dummy that takes value 1 if the buyer zip code has an average household income above the median value in the metropolitan area of Madrid, and 0 otherwise.[30] Table 9 shows zip codes with below median income reduced spending and number of transactions by 13.5 and 17.5 percent, respectively. Interestingly, buyer zip codes with average household income above the median in Madrid decreased spending value and number of transactions in the MC area by an additional 15.5 and 4.2 percent, respectively, more than treated zip codes with household incomes below the median. This implies that zip codes with higher levels of household incomes decreased their average transaction value of 11 percent relative to those zip codes with household income levels below the median. We do not find statistically significant evidence of changes in spending after March 2019 for above and below household income median zip codes.[31]

Next we investigate whether zip codes with more A vehicles or zip codes with a higher number of A vehicles per person are reducing spending the most given the nature of the policy restricting circulation of A vehicles in the MC area. We obtained car registration data from the city hall of Madrid for all zip codes inside the city of Madrid.[32] This means we are missing car registration data from zip codes inside the metropolitan area but outside the municipality of Madrid. We

[30] Data retrieved from https://www.agenciatributaria.es/AEAT/Contenidos_Comunes/La_Agencia_Tributaria/Estadisticas/Publicaciones/sites/irpfCodPostal/2016/jrubikf15b9305df2e5d53b0bbd20afaea102233fc84fd9.html and https://www.ine.es/experimental/atlas/experimental_atlas.htm.

[31] Appendix Tables D.2, D.3 and D.4 explore result heterogeneity further across seller sectors and buyer demographics such as age and gender.

[32] Data retrieved from https://datos.madrid.es/portal/site/egob/menuitem.c05c1f754a33a9fbe4b2e4b284f1a5a0/?vgnextoid=39cddd906cbee510VgnVCM1000001d4a900aRCRD&vgnextchannel=374512b9ace9f310VgnVCM100000171f5a0aRCRD&vgnextfmt=default.

Table 9: Result Heterogeneity by Zip Code Household Income

	(1) Value	(2) Transactions	(3) Transaction Value
Treatment	-0.135***	-0.175***	0.0399
	(0.0479)	(0.0352)	(0.0437)
Treatment High Income	-0.155***	-0.0416**	-0.114***
	(0.0402)	(0.0209)	(0.0292)
Treatment Post March 2019	0.0175	-0.00519	0.0227
	(0.0205)	(0.0156)	(0.0144)
Treatment High Income Post March 2019	-0.0209	0.00834	-0.0293**
	(0.0163)	(0.0108)	(0.0124)
Buyer-week-year FE	Yes	Yes	Yes
Seller-week-year FE	Yes	Yes	Yes
Buyer-seller-week FE	Yes	Yes	Yes
Observations	3404280	3404280	3404280

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Standard errors are clustered at the buyer-seller zip code pair level. The dependent variable is in logs at the seller-zip code by buyer-zip code level in a given week. The variable Treatment takes value 1 when (1) a seller-zip code is within the MC area and the MC regulations are in place, and (2) the buyer-zip code is outside the MC area, and 0 otherwise. The variable Treatment Post March 2019 takes value 1 when the dummy Treatment takes value 1 and the week is after March 2019.

create two dummy variables dividing zip codes by whether their number of A vehicles and number of A vehicles per person are above the respective city median values, and interact these dummies with our *Treatment* variables. Results in Table 10 show that buyer zip codes with less cars reduced spending and number of transactions by 15.6 and 13.5 percent, respectively, with further decreases after March 2019. Buyer zip codes with more cars reduced the number of transactions, but did not reduce spending. We find different results in columns 4 to 6 once we account for zip code population and divide zip codes above and below the median number of vehicles per person. Those zip codes with higher number of cars per person appear to have reduced spending and transactions by 21.5 and 8 percent, respectively, relative to those zip codes with lower number of cars per person. This set of results in columns 4, 5 and 6 in Table 10 is intuitive in that those zip codes were car ownership is widespread are more likely to be affected by the MC policy.[33]

[33] Using the car registration data, we find no evidence that the fleet of cars in areas further away from the city center is "dirtier," what would lead to a stronger bite of the policy for

Table 10: Result Heterogeneity by Zip Code Number of Cars

	(1) Value	(2) Transactions	(3) Transaction Value	(4) Value	(5) Transactions	(6) Transaction Value
Treatment	-0.156***	-0.135***	-0.0203	0.0806	-0.101***	0.182***
	(0.0540)	(0.0371)	(0.0485)	(0.0503)	(0.0353)	(0.0445)
Treatment High Cars	0.247***	-0.0116	0.259***			
	(0.0413)	(0.0270)	(0.0330)			
Treatment Post March 2019	-0.0609***	-0.0444***	-0.0164	-0.0208	-0.00746	-0.0133
	(0.0227)	(0.0172)	(0.0164)	(0.0208)	(0.0162)	(0.0152)
Treatment High Cars Post March 2019	0.0626***	0.0448***	0.0178			
	(0.0185)	(0.0141)	(0.0149)			
Treatment High Cars pp				-0.215***	-0.0795***	-0.135***
				(0.0412)	(0.0266)	(0.0346)
Treatment High Cars pp Post March 2019				-0.0150	-0.0273*	0.0123
				(0.0185)	(0.0142)	(0.0147)
Buyer-week-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Seller-week-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Buyer-seller-week FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1535112	1535112	1535112	1535112	1535112	1535112

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Standard errors are clustered at the buyer-seller zip code pair level. The dependent variable is in logs at the seller-zip code by buyer-zip code level in a given week. The variable Treatment takes value 1 when (1) a seller-zip code is within the MC area and the MC regulations are in place, and (2) the buyer-zip code is outside the MC area, and 0 otherwise. The variable Treatment Post March 2019 takes value 1 when the dummy Treatment takes value 1 and the week is after March 2019.

A third set of robustness checks is concerned with the fact that differences in transportation costs across zip codes may have changed differently after MC. Because the policy restricts driving into the city center, consumers now could consider other means of transportation. Those living in zip codes closer to the MC area are more likely to be able to switch with ease to walking or taking public transport. By contrast, consumers living further away from the MC area might find it more difficult to substitute their car for other means of transportation, as they are not able to walk to the city center and their access to public transport may be less convenient. In Appendix Table D.5, we use estimates on travel times from

residents further away from the MC area. We implement this test by regressing distance to the center on the share of the affected private category A cars in each neighborhood. One additional kilometer of distance is associated with an increase in the share of cars affected by MC by only 0.003 (0.2% of the mean). This estimate is not only economically but also statistically highly insignificant ($t = 0.84$).

the Google Maps Distance API to show that the relative time loss when switching from car to public transport is indeed larger for zip codes located farther away from the city center. Therefore, one would expect the impact of MC on consumers living farther away from the city to be more severe than for those living closer to the MC area.

To address this concern, Table 11 presents further evidence consistent with the fact that an increase in transportation costs drives the reduction in spending and number of transactions found in Table 7. Using the Google Maps Distance API, we calculate travel times by car and public transport from the centroid of each zip code to the geographic centroid of the MC area. We divide zip codes in two ways: those above and below the median of the absolute increase in travel time, and those above and below the median of the percentage increase in travel time. Columns 1 to 3 show that those zip codes with a higher absolute increase in travel time when switching from private to public transportation reduce their spending and number of transactions further than those with lower increases in travel time. Our findings in columns 4 to 6 are consistent with those in columns 1 to 3 in that we show those with higher percentage increase in travel time reduce spending and number of transactions more than those with lower percentage increase in travel time. In both cases, consumers in zip codes with higher absolute and percentage increases also reduce the average transaction value. We find no evidence of a change in spending behavior after March 2019 across different groups of zip codes.

Although Table 11 shows those zip codes with worse access to public transportation are affected most by MC, there could be variation in access to public transportation within a zip code. In order to study the potential impact of within-zip code variation in access to public transportation, we collected the location of all public transportation stops (subway, bus, train and tramway) across the metropolitan area of Madrid at the census tract level.[34] Using these data, we are able to create two variables that account for public transport access heterogeneity at the zip code level. First, we count the number of public transportation stops per census tract and calculate the standard deviation of the number of stops across census tracts within a zip code. Second, we divide the standard deviation by the mean number of public transportation stops in each zip code across census tracts. We generate two dummy variables that (1) take value 1 if a zip code has an absolute dispersion of public transportation stops above the median zip code, and 0 otherwise, and (2) take value 1 if a zip code has a dispersion normalized by its mean above the median zip code, and 0 otherwise, respectively. Our findings in

[34] See source at https://datos.crtm.es/

Table 11: Result Heterogeneity by Zip Code Increase in Travel Time

	(1) Value	(2) Transactions	(3) Transaction Value	(4) Value	(5) Transactions	(6) Transaction Value
Treatment	-0.0940*	-0.155***	0.0613	-0.135***	-0.166***	0.0312
	(0.0480)	(0.0356)	(0.0444)	(0.0487)	(0.0358)	(0.0447)
Treatment High Increase	-0.207***	-0.0702***	-0.136***			
	(0.0391)	(0.0206)	(0.0285)			
Treatment Post March 2019	0.00531	-0.00351	0.00882	0.0114	-0.00194	0.0134
	(0.0199)	(0.0154)	(0.0139)	(0.0201)	(0.0156)	(0.0141)
Treatment High Increase Post March 2019	0.00269	0.00535	-0.00265			
	(0.0161)	(0.0107)	(0.0123)			
Treatment High % Increase				-0.131***	-0.0504**	-0.0809***
				(0.0397)	(0.0207)	(0.0289)
Treatment High % Increase Post March 2019				-0.00860	0.00245	-0.0111
				(0.0162)	(0.0108)	(0.0123)
Buyer-week-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Seller-week-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Buyer-seller-week FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3458422	3458422	3458422	3458422	3458422	3458422

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Standard errors are clustered at the buyer-seller zip code pair level. The dependent variable is in logs at the seller-zip code by buyer-zip code level in a given week. The variable Treatment takes value 1 when (1) a seller-zip code is within the MC area and the MC regulations are in place, and (2) the buyer-zip code is outside the MC area, and 0 otherwise. The variable Treatment Post March 2019 takes value 1 when the dummy Treatment takes value 1 and the week is after March 2019.

columns 1 to 3 of Table 12 show that those zip codes with high dispersion of access to public transportation reduced spending and number of transactions more than those zip codes with lower dispersion of access to public transportation. This finding is consistent with previous results where most unequal access to public transportation may reduce spending in otherwise similar zip codes. Interestingly, columns 4 to 6 show that those zip codes with higher levels of normalized dispersion reduced spending and number of transactions, but they did so less than those zip codes with lower levels of normalized dispersion. These results in columns 4 to 6 imply those zip codes with less stops across census tracts reduced their spending and transactions after MC more than those zip codes with more stops across their census tracts holding constant their levels of absolute dispersion of access to public transportation.

Table 12: Result Heterogeneity by Zip Code Public Transportation Availability

	(1) Value	(2) Transactions	(3) Transaction Value	(4) Value	(5) Transactions	(6) Transaction Value
Treatment	-0.156***	-0.174***	0.0175	-0.262***	-0.195***	-0.0668
	(0.0468)	(0.0350)	(0.0433)	(0.0524)	(0.0365)	(0.0463)
Treatment High SD Stops	-0.117***	-0.0461**	-0.0705**			
	(0.0429)	(0.0216)	(0.0309)			
Treatment Post March 2019	0.00810	-0.00174	0.00984	0.0208	0.00893	0.0119
	(0.0198)	(0.0150)	(0.0140)	(0.0229)	(0.0163)	(0.0163)
Treatment High SD Stops Post March 2019	-0.00311	0.00264	-0.00575			
	(0.0171)	(0.0111)	(0.0129)			
Treatment High SD/Mean Stops				0.0862**	0.00227	0.0840***
				(0.0414)	(0.0212)	(0.0297)
Treatment High SD/Mean Stops Post March 2019				-0.0217	-0.0147	-0.00696
				(0.0180)	(0.0114)	(0.0137)
Buyer-week-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Seller-week-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Buyer-seller-week FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3433534	3433534	3433534	3433534	3433534	3433534

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Standard errors are clustered at the buyer-seller zip code pair level. The dependent variable is in logs at the seller-zip code by buyer-zip code level in a given week. The variable Treatment takes value 1 when (1) a seller-zip code is within the MC area and the MC regulations are in place, and (2) the buyer-zip code is outside the MC area, and 0 otherwise. The variable Treatment Post March 2019 takes value 1 when the dummy Treatment takes value 1 and the week is after March 2019.

A final concern with our triple difference specification is the potential existence of different pretrends in spending in stores located in the MC area by consumers residing outside MC. In fact, different trends in the propensity of different buyer-zip codes to buy in each seller-zip code could invalidate the results in Table 7. We address this concern in a number of different ways. First, Figure 5a and Figure 5b in Section 5.1 show no evidence of differences in pretrends across treated buyer-seller zip codes and other pairs. Second, we design a number of falsification tests where we define an additional falsification variable which assumes that the introduction of MC took place approximately 4, 6, and 8 weeks before it actually did (weeks 41, 43 and 45 instead of the real week of introduction of the policy in week 49 of 2018). While we do not show these results here, we find no effects. Therefore, we rule out differential trends and anticipatory effects that might induce consumers to bring forward consumption in the MC area as a result of the imminent increase in transaction costs as potential explanations.[35]

Our third and final falsification test consists of randomly picking six zip codes as pseudo-MC area and run the same specification as in equation (2) with weekly spending as dependent variable under two restrictions: zip codes cannot be in the original MC area and zip codes must be among the top 75% seller zip codes in terms of spending. We repeat this exercise 500 times. MacKinnon and Webb (2020) argue that randomization inference based on t-statistics works better than based on regression coefficients when there is more than one treated group and the size of the treated and control groups differs. These conditions seem to adjust to our empirical setting as we have more than one treated group (we have six treated zip codes) and zip codes within Madrid are heterogeneous in size and demographics. The zip codes that are treated in our setting a) have very high sales volume and b) have consumers from all over the city. Neither is true for many of the control zip codes. This automatically leads to a lot of noise and thereby to some extremely large coefficients (both positive and negative) when randomizing treatment across non-treated zip codes. By keeping only the top 75% spending zip codes, we reduce some of this problem but not all. By focusing on t-statistics instead of the regression coefficients, we take into account that these large noisy estimates have a larger standard error and therefore discipline the distribution of tests when replacing a coefficient by its t-statistic. Our results in Table 7 show a coefficient of -0.206 with a t-statistic 4.48. Out of the 500 draws, only 19 out 500 t-statistics are smaller than 4.48 which implies a p-value below 5%.[36]

In summary, we have made two important observations in the previous section. First, transportation costs matter as MC affects consumer behavior. The increase in transportation costs decreases consumer spending in brick-and-mortar establishments. Second, when transportation costs increase, there seems to be substitution from brick-and-mortar to online spending. We examine these general mechanisms in this section and effectively show that consumers in zip codes with

[35] These results are available upon request.

[36] Another potential concern arises from the incidence of zeros in trade flows between some zip code pairs. While in the paper we show results of adding one to the dependent variable of interest to avoid dropping observations once we take logs, we obtain similar findings to those in Table 7 when using Poisson Pseudo Maximum Likelihood. This method accommodates zero trade flows with no transformations of the dependent variables since these are in levels (Santos Silva and Tenreyro, 2006). Results are available upon request.

larger transaction costs and larger changes in transaction costs decreased their spending more than those with smaller transaction costs.[37]

As mentioned earlier, MC might not only affect transportation costs for a group of consumers but also increase the attractiveness of Madrid's city center for all shoppers. The triple differences strategy accounts for this confounding factor by including seller-specific time fixed effects and by comparing the behavior of consumers living inside and outside the MC area. When including such fixed effects, our results show that consumers living outside the MC area decrease their consumption in the MC area relative to those living inside. However, this strategy precludes the quantification of the potential increase of the attractiveness of the MC area for all consumers.[38]

6 Conclusion

This paper analyzes the benefits and costs of the introduction of constraints to vehicle circulation in the center of Madrid. By substantially restricting access by car, transportation costs increase for those consumers living outside the area affected by the policy, potentially discouraging consumption spending in that particular area. We show that the regulation had the intended effect of reducing traffic congestion in the affected area, and consequently we observe a significant decrease in air pollution. This first set of results clearly states direct benefits from the implementation of MC in the city of Madrid.

The improvement in air quality was economically highly significant, likely due to its strong bite compared to traffic restrictions in other cities. We can approximate the health benefits based on elasticities provided by prior research. Numbers from Currie and Walker (2011) can be used to estimate effects on premature births and low birth weight (LBW), and from He et al. (2019) for the effects on cardiovascular hospital admissions, respiratory hospital admissions, and cardiovascular and

[37]Although not shown here, we find find that consumption exhibits gravity in our setting. Spending decreases with distance across buyer-seller zip codes pairs. This is important for two distinct purposes. First, we show that transportation costs within a city matter. Second, because buyers located furthest away from the MC area were buying little in the MC area and the introduction of MC increased transportation costs of those buyers located further away from the MC area to a greater extent, we must include buyer-seller zip code fixed effects to avoid negative bias in the estimation of the effect of MC on consumption spending.

[38]We can examine this pathway in a simple difference-in-difference specification, comparing sales inside and outside the regulated area. Nevertheless, such specification cannot control for unobserved supply shocks in different areas and demand shocks for different groups of consumers. Thus, we should be careful in drawing strong conclusions from a difference-in-difference specification of sales.

respiratory mortality. Based on the estimated incidence of these outcomes inside the MC area in 2017, our estimates imply that MC has led to 30 fewer premature births, 43 fewer LBW births, 300 fewer respiratory hospital admissions, and 319 fewer cardiovascular hospital admissions per year. Evaluated at the average cost incurred in Spain, these imply annual medical savings of around €3.4 million, i.e. 0.4% of LBW, respiratory and cardiovascular hospital expenditures in the Spanish region of Madrid.[39] In addition, evaluated at the elasticity estimate of He et al. (2019) for cardiovascular and respiratory mortality, MC has saved 88 lives per year.[40]

However, our data allow for further investigation on the impact of the policy on economic activity. In particular, we use credit card transaction data from a large bank to examine whether consumers affected by the regulation reduced consumption spending in the city center of Madrid as a result of the increase in transportation costs. The granularity of our data grants the identification of purchases of all possible pairs of buyer zip codes and seller zip codes in the city of Madrid. Our findings show brick-and-mortar spending and transactions by the directly affected consumers decreased while online spending and transactions by the affected consumers increased. The effect of the policy is larger for those zip codes where buyers face larger transportation constraints. This set of findings are consistent with substitution from brick-and-mortar to online spending when consumers face larger transportation costs.

Driving bans impose a cost on consumers by making shopping in brick-and-mortar establishments less attractive. While air quality improvements are significant and provide large benefits, brick-and-mortar commerce can be negatively affected. Our results show that, on aggregate, consumers substitute to online purchases, which partly compensates the loss in brick-and-mortar spending. However, these substitutions are usually made at different types of sellers so that a driving ban might have unintended distributional effects on smaller businesses.

Thus, our paper contributes to the literature in a number of ways. On the one hand, we provide estimates of the impact of a restrictive environmental policy that affected a very high proportion of vehicles in a major city. On the other hand, our paper also provides evidence of the impact of environmental policies on economic activity, more specifically, on spending and number of transactions of consumers in establishments directly affected by the policy. Most importantly, we offer evi-

[39]The Spanish region of Madrid has 7 million people. The metropolitan area of Madrid is a subregion within the region of Madrid with 4.8 million people. See https://es.wikipedia.org/wiki/%C3%81rea_metropolitana_de_Madrid

[40]The data sources and calculations are detailed in Appendix E.

dence that these effects are not homogeneous and vary along different dimensions. A novel result in our analysis is the potential role played by e-commerce in attenuating the impact of environmental regulation, and its implication for policy makers regarding e-commerce and online transactions. Future research on the impact of environmental policies, regardless of the type of pollution regulated, should aim to provide direct evidence of their cost through diminished economic activity. Similarly, understanding the distributional effects of such policies is a crucial part of the information necessary for the design of future environmental regulations and their respective policy implementations. Furthermore, our results speak about the relevant role that e-commerce may play in smoothing the impact of increases in consumer transportation costs generated by other factors than environmental regulations. For instance, future research should study how consumers resorted to online purchasing during lockdown periods through the Covid-19 pandemic and how e-commerce adoption allowed establishments to weather such critical situation.

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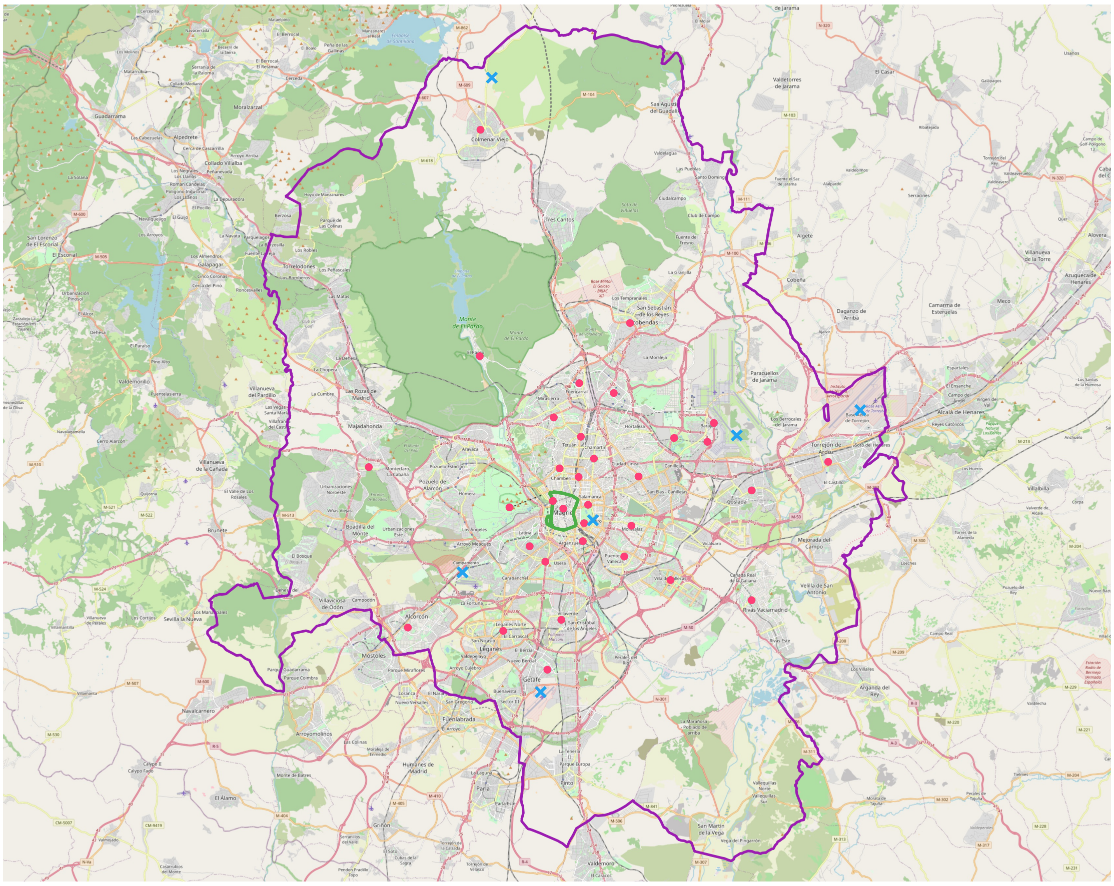
A Maps

FIGURE A.1: Map of stations



Notes: The map displays the locations of the air quality monitoring stations within the city of Madrid. The pollution monitoring stations appear with pink circles in the map whereas weather stations appear in blue crosses. Source: OpenStreetMap.

B Summary statistics

Table B.1 provides descriptive statistics at the traffic monitor level for the same variables reported in Table 2.

Table B.1: Descriptive statistics on weather conditions

	Mean (1)	SD (2)	Min (3)	Max (4)	Obs (5)
Temperature [°C]	15.72	7.54	3.39	30.87	663,497
Precipitation [0.1mm]	10.23	17.68	0.00	131.43	663,497
Cloud cover [okta]	3.42	1.75	0.00	7.57	663,497
Sunshine [h]	8.35	2.94	1.13	13.41	663,497
Pressure [hPa]	1017.03	6.03	998.21	1035.54	663,497
Humidity [%]	57.35	14.46	26.29	90.29	663,497
Wind speed [0.1 m/s]	19.92	8.42	0.43	75.43	663,497
$0° \leq$ Wind direction $< 45°$	0.19	0.18	0.00	1.00	663,497
$45° \leq$ Wind direction $< 90°$	0.18	0.19	0.00	0.71	663,497
$90° \leq$ Wind direction $< 135°$	0.10	0.14	0.00	0.86	663,497
$135° \leq$ Wind direction $< 180°$	0.05	0.09	0.00	0.57	663,497
$180° \leq$ Wind direction $< 225°$	0.10	0.14	0.00	0.86	663,497
$225° \leq$ Wind direction $< 270°$	0.22	0.21	0.00	1.00	663,497
$270° \leq$ Wind direction $< 315°$	0.12	0.15	0.00	0.86	663,497
$315° \leq$ Wind direction $< 360°$	0.05	0.10	0.00	0.86	663,497

Notes: The table shows descriptive statistics on weather conditions at each traffic station, where weekly weather is obtained from the closest weather monitor.

C Alternative specifications of congestion and pollution analysis

Table C.1 replicates the specifications in Table 5 with standard errors clustered at the zip code level.

Table C.1: Effects on traffic levels

	Vehicles per hour (1)	Time occupied [%] (2)	Log Vehicles per hour (3)	Log Time occupied (4)
Madrid Central	-56.51***	-2.173***	-0.161***	-0.210***
	(11.23)	(0.611)	(0.0107)	(0.0391)
Madrid Central Post March 2019	6.005	1.354***	0.0357***	0.104***
	(4.310)	(0.395)	(0.00767)	(0.0262)
Location-Week FE	Yes	Yes	Yes	Yes
Year-Week FE	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes
Mean dep. var.	456.1	6.567	5.646	1.493
N×T	646819	646493	646629	642111
N	3966	3966	3966	3945

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Standard errors are clustered at the zip code level. The variable Madrid Central takes value 1 when a station is located in the indicated area and the MC regulations are in place, and 0 otherwise. The variable Madrid Central Post March 2019 takes value 1 in the same case and when the week is after March 2019. The weather controls are second order polynomials of temperature, precipitation, cloud cover, humidity, pressure and wind speed, as well as wind direction indicators interacted with station indicators.

Table C.2 replicates the specifications in Table 5 including a dummy for whether the traffic monitoring station is located in the surroundings of the MC area.

Table C.2: Effects on traffic levels: Spillovers

	Vehicles per hour (1)	Time occupied [%] (2)	Log Vehicles per hour (3)	Log Time occupied (4)
Madrid Central	-60.62***	-2.221**	-0.167***	-0.212***
	(13.89)	(0.947)	(0.0273)	(0.0515)
Madrid Central Post March 2019	7.595	1.393***	0.0380***	0.109***
	(5.072)	(0.514)	(0.0139)	(0.0383)
Surroundings	-25.01***	-0.289*	-0.0385***	-0.0105
	(3.676)	(0.169)	(0.00611)	(0.0169)
Surroundings Post March 2019	8.368***	0.234*	0.0117**	0.0305***
	(2.879)	(0.130)	(0.00490)	(0.0112)
Location-Week FE	Yes	Yes	Yes	Yes
Year-Week FE	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes
Mean dep. var.	456.1	6.567	5.646	1.493
N×T	646819	646493	646629	642111
N	3966	3966	3966	3945

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Standard errors are clustered at the station level. The variables take value 1 when a station is located in the indicated area and the MC regulations are in place, and 0 otherwise. The variables referring to Post March 2019 takes value 1 in the same case and when the week is after March 2019. The weather controls are second order polynomials of temperature, precipitation, cloud cover, humidity, pressure and wind speed, as well as wind direction indicators interacted with station indicators.

Table C.3 replicates the exercise in Table 6 for maxima of pollution.

TABLE C.3: Effects on Air Pollution Levels: Effect on maxima

	Log NO_2 8-hour max	Log NO_2 max
	(1)	(2)
Madrid Central	-0.158***	-0.112***
	(0.0146)	(0.0144)
Madrid Central		
Post March 2019	-0.225***	-0.189***
	(0.0171)	(0.0145)
Station-Week FE	Yes	Yes
Year-Week FE	Yes	Yes
Weather Controls	Yes	Yes
Mean dep. var.	3.989	4.340
N×T	7650	7657
N	33	33

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Standard errors are clustered at the station level. The variables take value 1 when a station is located in the indicated area and the MC regulations are in place, and 0 otherwise. The variables referring to Post March 2019 takes value 1 in the same case and when the week is after March 2019. The weather controls are second order polynomials of temperature, precipitation, cloud cover, humidity, pressure and wind speed, as well as wind direction indicators interacted with station indicators.

Table C.4 replicates the specifications in Table 5 at the daily level, including day fixed effects.

Table C.4: Effects on traffic levels

	Vehicles per hour (1)	Time occupied [%] (2)	Log Vehicles per hour (3)	Log Time occupied (4)
Madrid Central	-51.68***	-2.136**	-0.155***	-0.203***
	(13.13)	(0.944)	(0.0268)	(0.0505)
Madrid Central Post March 2019	1.460	1.208***	0.0338***	0.104***
	(4.922)	(0.454)	(0.0128)	(0.0345)
Location-Week FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes
Mean dep. var.	451.9	6.555	5.609	1.425
N×T	4682163	4679775	4679573	4645792
N	204925	204902	204873	203890

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Standard errors are clustered at the zip code level. The variables take value 1 when a station is located in the indicated area and the MC regulations are in place, and 0 otherwise. The variables referring to Post March 2019 takes value 1 in the same case and when the week is after March 2019. The weather controls are second order polynomials of temperature, precipitation, cloud cover, humidity, pressure and wind speed, as well as wind direction indicators interacted with station indicators.

Table C.5 replicates the specifications in Table 6 at the daily level, including day fixed effects.

Table C.5: Effects on Air Pollution Levels

	Log NO_2			$NO_2 > 40$		
	(1)	(2)	(3)	(4)	(5)	(6)
Madrid Central	-0.214***	-0.217***	-0.226***	-0.170***	-0.172***	-0.185***
	(0.0163)	(0.0176)	(0.0274)	(0.0126)	(0.0136)	(0.0214)
Madrid Central Post March 2019	-0.198***	-0.203***	-0.236***	-0.171***	-0.171***	-0.196***
	(0.0182)	(0.0192)	(0.0382)	(0.0179)	(0.0192)	(0.0247)
Surroundings		-0.0353	-0.0436		-0.0204	-0.0338
		(0.0406)	(0.0458)		(0.0266)	(0.0312)
Surroundings Post March 2019		-0.0513	-0.0841		-0.00615	-0.0306
		(0.0524)	(0.0615)		(0.0457)	(0.0480)
City of Madrid			-0.0117			-0.0187
			(0.0358)			(0.0250)
City of Madrid Post March 2019			-0.0450			-0.0335
			(0.0428)			(0.0299)
Station-Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes	Yes
Mean dep. var.	3.461	3.461	3.461	0.391	0.391	0.391
N×T	53506	53506	53506	53506	53506	53506
N	1716	1716	1716	1716	1716	1716

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Standard errors are clustered at the zip code level. The variables take value 1 when a station is located in the indicated area and the MC regulations are in place, and 0 otherwise. The variables referring to Post March 2019 takes value 1 in the same case and when the week is after March 2019. The weather controls are second order polynomials of temperature, precipitation, cloud cover, humidity, pressure and wind speed, as well as wind direction indicators interacted with station indicators.

Table C.6 replicates the specifications in Table 5 with the interaction of temperature, wind speed, and precipitation decile indicators.

Table C.6: Effects on traffic levels

	Vehicles per hour (1)	Time occupied [%] (2)	Log Vehicles per hour (3)	Log Time occupied (4)
Madrid Central	-55.57***	-2.132**	-0.160***	-0.209***
	(13.90)	(0.947)	(0.0273)	(0.0516)
Madrid Central Post March 2019	5.678	1.336***	0.0337**	0.105***
	(5.076)	(0.514)	(0.0139)	(0.0383)
Location-Week FE	Yes	Yes	Yes	Yes
Year-Week FE	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes
Mean dep. var.	456.1	6.567	5.646	1.493
N×T	646815	646489	646625	642107
N	3966	3966	3966	3945

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Standard errors are clustered at the zip code level. The variables take value 1 when a station is located in the indicated area and the MC regulations are in place, and 0 otherwise. The variables referring to Post March 2019 takes value 1 in the same case and when the week is after March 2019. The weather controls are interactions of temperature, precipitation, and wind speed decile indicators.

Table C.7 replicates the specifications in Table 6 with the interaction of temperature, wind speed, and precipitation decile indicators.

Table C.7: Effects on Air Pollution Levels

	Log NO_2			$NO_2 > 40$		
	(1)	(2)	(3)	(4)	(5)	(6)
Madrid Central	-0.178***	-0.181***	-0.155***	-0.156***	-0.156***	-0.138***
	(0.0183)	(0.0206)	(0.0347)	(0.0139)	(0.0156)	(0.0280)
Madrid Central Post March 2019	-0.208***	-0.211***	-0.247***	-0.171***	-0.172***	-0.207***
	(0.0179)	(0.0191)	(0.0432)	(0.0221)	(0.0242)	(0.0393)
Surroundings		-0.0158	0.00986		-0.00476	0.0138
		(0.0398)	(0.0482)		(0.0311)	(0.0385)
Surroundings Post March 2019		-0.0230	-0.0588		-0.00201	-0.0368
		(0.0563)	(0.0684)		(0.0524)	(0.0603)
City of Madrid			0.0272			0.0197
			(0.0332)			(0.0268)
City of Madrid Post March 2019			-0.0381			-0.0371
			(0.0435)			(0.0372)
Station-Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes	Yes
Mean dep. var.	3.523	3.523	3.523	0.393	0.393	0.393
N×T	7591	7591	7591	7591	7591	7591
N	33	33	33	33	33	33

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Standard errors are clustered at the zip code level. The variables take value 1 when a station is located in the indicated area and the MC regulations are in place, and 0 otherwise. The variables referring to Post March 2019 takes value 1 in the same case and when the week is after March 2019. The weather controls are interactions of temperature, precipitation, and wind speed decile indicators.

Table C.8 replicates the specifications in Table 5 while allowing for heterogeneous effects of holidays at the station level.

Table C.8: Effects on traffic levels

	Vehicles per hour (1)	Time occupied [%] (2)	Log Vehicles per hour (3)	Log Time occupied (4)
Madrid Central	-55.27***	-2.171**	-0.158***	-0.206***
	(13.92)	(0.947)	(0.0273)	(0.0515)
Madrid Central Post March 2019	2.962	1.349***	0.0287**	0.0942**
	(5.022)	(0.512)	(0.0139)	(0.0381)
Location-Week FE	Yes	Yes	Yes	Yes
Year-Week FE	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes
Mean dep. var.	456.1	6.567	5.646	1.493
N×T	646819	646493	646629	642111
N	3966	3966	3966	3945

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Standard errors are clustered at the zip code level. The variables take value 1 when a station is located in the indicated area and the MC regulations are in place, and 0 otherwise. The variables referring to Post March 2019 takes value 1 in the same case and when the week is after March 2019. The weather controls are second order polynomials of temperature, precipitation, cloud cover, humidity, pressure and wind speed, as well as wind direction indicators interacted with station indicators.

Table C.9 replicates the specifications in Table 6 while allowing for heterogeneous effects of holidays at the station level.

Table C.9: Effects on Air Pollution Levels

	Log NO_2			$NO_2 > 40$		
	(1)	(2)	(3)	(4)	(5)	(6)
Madrid Central	-0.186***	-0.189***	-0.193***	-0.168***	-0.171***	-0.179***
	(0.0155)	(0.0169)	(0.0283)	(0.0128)	(0.0140)	(0.0202)
Madrid Central Post March 2019	-0.232***	-0.236***	-0.268***	-0.166***	-0.166***	-0.189***
	(0.0188)	(0.0197)	(0.0380)	(0.0187)	(0.0201)	(0.0228)
Surroundings		-0.0295	-0.0325		-0.0231	-0.0311
		(0.0363)	(0.0429)		(0.0265)	(0.0299)
Surroundings Post March 2019		-0.0408	-0.0731		0.00418	-0.0187
		(0.0561)	(0.0640)		(0.0438)	(0.0447)
City of Madrid			-0.00426			-0.0109
			(0.0340)			(0.0242)
City of Madrid Post March 2019			-0.0435			-0.0309
			(0.0390)			(0.0264)
Station-Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes	Yes
Mean dep. var.	3.521	3.521	3.521	0.392	0.392	0.392
N×T	7657	7657	7657	7657	7657	7657
N	33	33	33	33	33	33

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Standard errors are clustered at the zip code level. The variables take value 1 when a station is located in the indicated area and the MC regulations are in place, and 0 otherwise. The variables referring to Post March 2019 takes value 1 in the same case and when the week is after March 2019. The weather controls are second order polynomials of temperature, precipitation, cloud cover, humidity, pressure and wind speed, as well as wind direction indicators interacted with station indicators.

Table C.10 replicates the exercise in Table 6 with station-specific trends.

TABLE C.10: Regression of NO_2 levels with station-specific trends

	Log NO_2			$NO_2 > 40$		
	(1)	(2)	(3)	(4)	(5)	(6)
Madrid Central	-0.183***	-0.185***	-0.203***	-0.183***	-0.184***	-0.197***
	(0.0153)	(0.0167)	(0.0344)	(0.0144)	(0.0139)	(0.0228)
Madrid Central Post March 2019	-0.225***	-0.225***	-0.257***	-0.164***	-0.164***	-0.183***
	(0.0189)	(0.0188)	(0.0413)	(0.0194)	(0.0194)	(0.0248)
Surroundings		-0.0240	-0.0273		-0.0145	-0.0300
		(0.0489)	(0.0433)		(0.0432)	(0.0587)
Surroundings Post March 2019			-0.0638			-0.0129
			(0.0657)			(0.0444)
City of Madrid			-0.0273			-0.0173
			(0.0388)			(0.0253)
City of Madrid Post March 2019			-0.0370			-0.0255
			(0.0425)			(0.0267)
Station-Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes	Yes
Mean dep. var.	3.521	3.521	3.521	0.392	0.392	0.392
N×T	7657	7657	7657	7657	7657	7657
N	33	33	33	33	33	33

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Standard errors are clustered at the station level. The variables take value 1 when a station is located in the indicated area and the MC regulations are in place, and 0 otherwise. The weather controls are second order polynomials of temperature, precipitation, cloud cover, humidity, pressure and wind speed, as well as wind direction indicators interacted with station indicators.

D Alternative specifications of the consumption spending analysis

Table D.1 replicates the specification in Table 8 with different dependent variables, namely the share of online revenue, share of online transactions and ratio of transaction values. The results are showing that decreases in brick-and-mortar transactions and increases in online transactions are taking place within buyer-seller zip code pairs.

TABLE D.1: Online Shares

	Share online revenue (1)	Share online transactions (2)	Ratio transaction values (3)
Treatment	3.380***	1.434***	-0.0141
	(0.675)	(0.495)	(0.143)
Buyer-week-year FE	Yes	Yes	Yes
Seller-week-year FE	Yes	Yes	Yes
Buyer-seller-week FE	Yes	Yes	Yes
Observations	3,460,968	3,460,968	3,460,968

Notes: Dependent variable: Percentage share of online revenue, online number of transactions and ratio between online and B&M transaction values. *** denotes significance at 1%, ** at 5%, and * at 10%. Standard errors are clustered at the buyer-seller pair level.

In Tables D.2, D.3 and D.4, we explore result heterogeneity across seller sectors and buyer demographics such as age and gender. To do so, we use data from October 1st 2018 to June 30th 2019 where we are able to separate weekly transactions by sector destination in each zip code and also by age group and gender in each buyer zip code. It is interesting to see that there were no differences across genders, and only the oldest age groups seem to be statistically affected by MC. Aside from auto services, there does not seem to be a sector that is dramatically affected by the new policy.

Table D.2: Impact of Madrid Central by buyers' gender

	(1)	(2)	(3)	(4)	(5)	(6)
		Female			Male	
	Value	Transactions	Transaction value	Value	Transactions	Transaction value
Treatment	-0.0437	-0.0521**	0.00845	-0.0427	-0.0125	-0.0302
	(0.0535)	(0.0258)	(0.0357)	(0.0693)	(0.0282)	(0.0570)
Treatment Post March 2019	0.0219	-0.0440	0.0659*	-0.0685	-0.0387	-0.0297
	(0.0573)	(0.0320)	(0.0351)	(0.0762)	(0.0270)	(0.0621)
Buyer-week-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Seller-week-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Buyer-seller FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	532888	532888	532888	532888	532888	532888

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Standard errors are clustered at the buyer-seller pair level. The dependent variable is in logs at the seller-zip code by buyer-zip code level in a given week. The variable Treatment takes value 1 when (1) a seller-zip code is within the MC area and the MC regulations are in place, and (2) the buyer-zip code is outside the MC area, and 0 otherwise. The variable Treatment Post March 2019 takes value 1 when the dummy Treatment takes value 1 and the week is after March 2019.

Table D.3: Impact of Madrid Central by buyers' age

	(1)	(2)	(3)	(4)	(5)	(6)
	≤ 24			25-34		
	Value	Transactions	Transaction value	Value	Transactions	Transaction value
Treatment	0.168	0.124	0.0436	0.0657	0.0264	0.0394
	(0.161)	(0.0808)	(0.0846)	(0.0473)	(0.0288)	(0.0275)
Treatment Post March 2019	-0.139	-0.117*	-0.0219	0.00925	-0.0419	0.0511
	(0.126)	(0.0671)	(0.0630)	(0.0610)	(0.0326)	(0.0353)
Buyer-week-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Seller-week-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Buyer-seller FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	532888	532888	532888	532888	532888	532888

	(7)	(8)	(9)	(10)	(11)	(12)
	35-44			45-54		
	Value	Transactions	Transaction value	Value	Transactions	Transaction value
Treatment	-0.0275	-0.0552	0.0276	-0.0389	-0.0190	-0.0199
	(0.0640)	(0.0349)	(0.0398)	(0.0728)	(0.0405)	(0.0434)
Treatment Post March 2019	0.0529	-0.0365	0.0894	-0.0471	-0.0747**	0.0276
	(0.110)	(0.0597)	(0.0559)	(0.0711)	(0.0309)	(0.0471)
Buyer-week-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Seller-week-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Buyer-seller FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	532888	532888	532888	532888	532888	532888

	(13)	(14)	(15)	(16)	(17)	(18)
	55-64			> 65		
	Value	Transactions	Transaction value	Value	Transactions	Transaction value
Treatment	-0.129	-0.120**	-0.00883	-0.275*	-0.187***	-0.0880
	(0.120)	(0.0582)	(0.0695)	(0.142)	(0.0705)	(0.0777)
Treatment Post March 2019	-0.0219	-0.0392	0.0173	-0.268*	-0.126*	-0.143*
	(0.0694)	(0.0313)	(0.0470)	(0.146)	(0.0663)	(0.0845)
Buyer-week-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Seller-week-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Buyer-seller FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	532888	532888	532888	532888	532888	532888

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Standard errors are clustered at the buyer-seller pair level. The dependent variable is in logs at the seller-zip code by buyer-zip code level in a given week. The variable Treatment takes value 1 when (1) a seller-zip code is within the MC area and the MC regulations are in place, and (2) the buyer-zip code is outside the MC area, and 0 otherwise. The variable Treatment Post March 2019 takes value 1 when the dummy Treatment takes value 1 and the week is after March 2019.

Table D.4: Impact of Madrid Central by sellers' sector

	(1) Auto	(2) Bars and Restaurants	(3) Contents	(4) Fashion	(5) Food
Treatment	0.0316	0.0185	-0.403***	-0.178	0.0595
	(0.0974)	(0.0488)	(0.131)	(0.111)	(0.0899)
Treatment Post March 2019	-0.225*	0.0156	0.0719	-0.0581	0.000483
	(0.125)	(0.0456)	(0.0910)	(0.0831)	(0.102)
Buyer-week-year FE	Yes	Yes	Yes	Yes	Yes
Seller-week-year FE	Yes	Yes	Yes	Yes	Yes
Buyer-seller FE	Yes	Yes	Yes	Yes	Yes
Observations	317421	512109	298818	436293	500760

	(6) Health	(7) Home	(8) Hotel Services	(9) Hyper	(10) Leisure
Treatment	-0.0478	-0.160	0.00699	0.187	0.285**
	(0.147)	(0.107)	(0.175)	(0.156)	(0.132)
Treatment Post March 2019	-0.177	0.0225	-0.0979	0.433***	0.0495
	(0.117)	(0.119)	(0.0784)	(0.137)	(0.0980)
Buyer-week-year FE	Yes	Yes	Yes	Yes	Yes
Seller-week-year FE	Yes	Yes	Yes	Yes	Yes
Buyer-seller FE	Yes	Yes	Yes	Yes	Yes
Observations	498771	398619	28197	150579	328653

	(11) Other Services	(12) Sports and Toys	(13) Tech	(14) Transportation	(15) Travel	(16) Wellness and Beauty
Treatment	-0.126	-0.0414	-0.0681	0.166	-0.204	-0.106
	(0.102)	(0.125)	(0.0985)	(0.116)	(0.180)	(0.0996)
Treatment Post March 2019	-0.0957	-0.0704	0.00112	0.154	0.164	-0.367***
	(0.0989)	(0.104)	(0.135)	(0.110)	(0.128)	(0.0976)
Buyer-week-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Seller-week-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Buyer-seller FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	484146	322686	338247	387036	35334	481572

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Standard errors are clustered at the buyer-seller pair level. The dependent variable is in logs at the seller-zip code by buyer-zip code level in a given week. The variable Treatment takes value 1 when (1) a seller-zip code is within the MC area and the MC regulations are in place, and (2) the buyer-zip code is outside the MC area, and 0 otherwise. The variable Treatment Post March 2019 takes value 1 when the dummy Treatment takes value 1 and the week is after March 2019.

In Table D.5 we confirm that consumers living further away from the city center will find it harder to substitute to public transport. Using the Google Maps Distance API, we calculate travel times by car and public transport from the centroid of each zip code to the centroid of the MC area. We then calculate how much longer it takes to use public transport compared to using the car. Table D.5 shows that the time loss due to public transport usage is 22 minutes larger for zip codes outside the city of Madrid compared to zip codes inside the city of Madrid. The difference is significant at the 1% level.

Table D.5: Changes in Travel Time

	Transit disadvantage in minutes
Zip codes out of city	21.53***
	(2.52)
Observations	119

Notes: Dependent variable: Changes in travel time to the center of the MC area (in minutes). *** denotes significance at 1%, ** at 5%, and * at 10%. We regress the difference between travel time to MC by public transportation and car on a dummy if a zip code is out of city.

E Estimation of the health benefits of Madrid Central

This section explains in detail how we translate the air pollution reduction to approximate health benefits. The calculations are based on our estimate of a 41.7% reduction in NO_2 pollution.

The findings of Currie and Walker (2011) imply elasticities of 0.84 for the incidence of premature births and of 1.05 for the incidence of low birth weight (LBW). The setting of their study is the introduction of automatic toll stations (EZ-Pass) in the U.S. One should note that their results are only approximate as they are based on a single pollution monitor.

From He et al. (2019) we obtain estimated elasticities of 0.44 for cardiovascular hospital admission, 0.41 for respiratory hospital admissions, and 0.55 for cardiovascular and respiratory mortality. Here we need to assume that the findings from an emerging economy translate to an industrialized economy, as the setting of the study is São Paulo.

To translate these elasticities to the population living inside the MC area, we need to determine its baseline health. We obtain these measures at the level of the province of Madrid for January 2017. Total population size of the province[41] was 6,476,705 while 131,928 persons lived in central Madrid,[42] i.e. 2.04%. To approximate health outcomes inside the MC area, we apply this percentage to all health outcomes, making the highly simplifying assumption that population health is uniformly distributed.

In 2017, there were 4241 cases of premature[43] and 4794 cases of LBW birth[44] in the province of Madrid. Moreover, 11,862 persons died due to cardiovascular issues and 7008 due to respiratory issues.[45] In addition, 90,519 persons were admitted to a hospital with a respiratory diagnosis and 79,730 persons were admitted with a cardiovascular diagnosis.[46]

[41] https://www.ine.es/jaxiT3/dlgExport.htm?t=9687&L=0&nocab=1

[42] https://www.madrid.es/UnidadesDescentralizadas/UDCEstadistica/Nuevaweb/Publicaciones/Padr%C3%B3n%20Municipal%20de%20Habitantes/2017/Municipio.pdf

[43] https://www.ine.es/jaxi/dlgExport.htm?tpx=35724&path=/t20/e301/nacim/a2017/&file=03024.px&L=0

[44] https://www.ine.es/jaxi/dlgExport.htm?tpx=35725&path=/t20/e301/nacim/a2017/&file=03025.px&L=0

[45] https://www.ine.es/jaxi/dlgExport.htm?tpx=29966&path=/t15/p417/a2017/&file=02014.px&L=0&nocab=1

[46] https://www.ine.es/jaxi/dlgExport.htm?tpx=30106&path=/t15/p414/a2017/&file=02001.px&L=0

Multiplying these case counts with 2.04% and applying the elasticities, leads to the following annual estimates: MC has reduced the number of premature births by 30.2 and of LBW births by 42.8. It has led to 300.0 fewer cardiovascular hospital admissions, 318.9 fewer respiratory hospital admissions, and 88.0 fewer deaths.

To translate the reduction in premature or LBW births and in hospital admissions into savings for the health sector, we obtain information on average treatment costs from the Hospital Admission Registry of the National Health System.[47] The average treatment costs per admissions for respiratory diagnoses was €4219.49 and for cardiovascular diagnoses €5690.14.

Procedures due to prematurity or LBW cannot be distinguished, but here the average cost per treatment directly referring to either of these two conditions is €16,801.00. Not all premature or LBW infants require treatment, so we first need to estimate how many infants in the MC area required hospital treatment due to premature birth or LBW. According to the Hospital Admission Registry, 14,499 cases of hospital treatments due to LBW were registered in Spain. From the birth statistics on LBW we also know that around 16% of the children born in Spain prematurely or with LBW are from the province of Madrid. Combined with the population share in the center of Madrid we therefore expect 46.0 infants from the MC area required hospital treatment in 2017 and that Madrid Central reduced this number by 14.2.

The implied savings by the public health system are therefore estimated to be €338,186.72 for hospital treatments of infants, €1,706,893.52 for cardiovascular hospital admissions, and €1,345,776.33 for respiratory hospital admissions, i.e. almost €3.4 million per year.

The estimated hospital expenditures incurred by the health service of the Autonomous Community of Madrid for LBW, respiratory, and cardiovascular admissions, were €772,280.66, €7,780,053.29, and €9,241,183.18. This means that the Community's public health system saves around 0.4% compared to the 2017-levels of expenditures.

This does not account for the estimated mortality reduction of 62 fewer cases. Attributing a monetary value to the value of life is particularly difficult in our setting, at it is not unlikely that the most frail, with a short life expectancy, are most affected by air pollution (cf. Deryugina et al., 2019, for a discussion of the implications of "harvesting").

[47] https://www.sanidad.gob.es/estadEstudios/estadisticas/docs/CMBD/NORMA_ESTATAL_APR_GRD_V32_2017_Hosp_agudos.xlsx