Benefits and 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 congestion and pollution, but they may also unintentionally distort consumer spending decisions. By increasing transportation costs to ban-affected areas, driving restrictions could discourage consumption 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 a decrease of 15 percent in both congestion and pollution. Second, we rely on a unique dataset on credit card transactions detailing spending for each pair of buyer-seller zip codes to analyze how the driving ban changed consumption behavior. Although we find no significant effect on overall consumption spending inside the regulated area, our findings show that consumers affected by the regulation partially substitute their consumption spending from brick-and-mortar to online shopping. This suggests e-commerce may smooth the impact of changes in transportation costs due to environmental regulations.

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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 benefits and costs of such environmental policies. A typical policy to 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. This 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

[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).

regulation restricts entry of cars in the center of the city of Madrid (a zone that we will refer to as "MC area") to people living elsewhere. This policy raises a stark tradeoff. Lower emissions in the city center will be a direct benefit of these regulations. However, by restricting access by car, transportation 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. 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 traffic congestion and air pollution 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 the number of cars per hour in the MC area decreased by 14.7% and the concentration of nitrogen dioxide (NO_2), a harmful pollutant, decreased by 13.6% in the MC area. Moreover, we do not find any evidence of spillovers to areas adjacent to MC in terms of NO_2 but a reduction in traffic in close-by areas.

Second, we use data on 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 tenth week 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, (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 an 8.9% 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. Moreover, it appears that the increase in online spending is, statistically speaking, offsetting the decrease in brick-and-mortar spending. 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.

Additionally, our triple differences strategy accounts for the possibility that MC may not only have affected transportation costs for a group of consumers but also increased the attractiveness of Madrid's city center for all shoppers. Our specification allows for seller-specific shocks and compares the behavior of consumers living inside and outside the MC area. This precludes the identification of the potential increase of the attractiveness of the MC area for all consumers. We can examine this pathway in a simple difference-in-difference specification, comparing sales inside and outside the regulated area. We find no impact of MC on sales when using data aggregated at the seller-zip code level. Together with the previous results, this suggests the attractiveness of the MC area does not decrease.

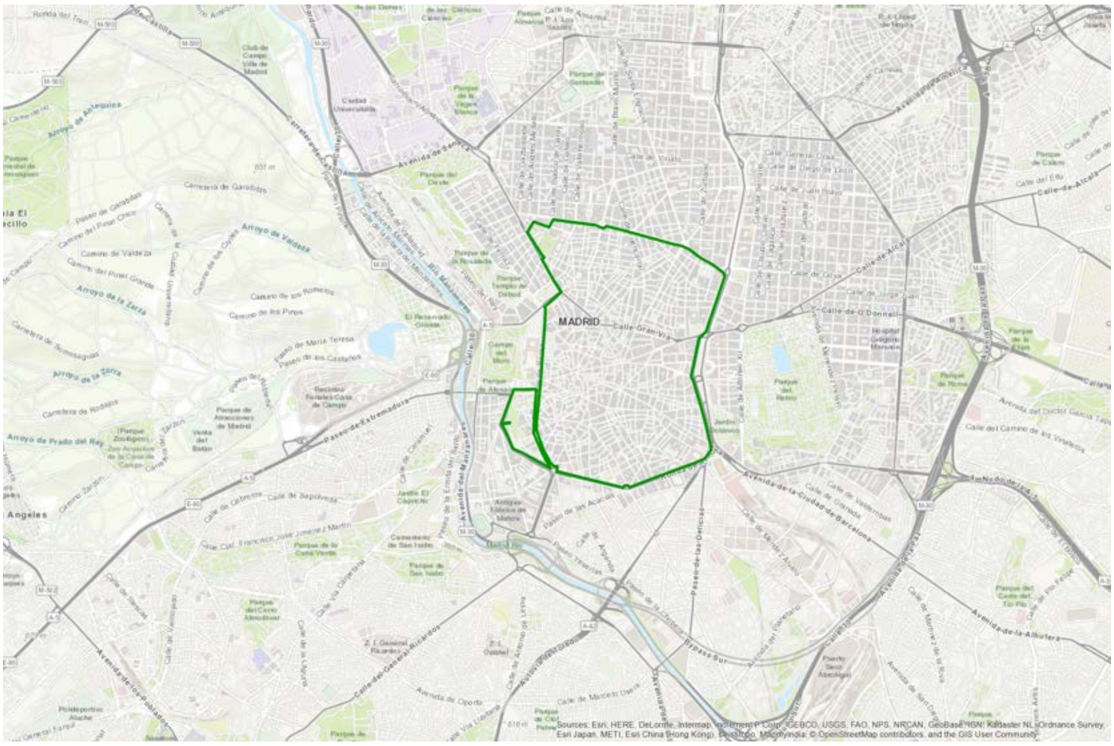
Although a large number of papers investigate the health and air quality benefits of different versions of driving bans and low emission zones, only a few papers study the effects on economic outcomes such as labor supply decisions and local commerce. Most recently, Blackman et al. (2018) and Blackman 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 paper closest 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 those 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. Examples of cities that have implemented similar traffic-related policies and their respective studies are Mexico City (Eskeland and Feyzioglu, 1997; Davis, 2008; Salas, 2010; Gallego et al., 2013; Oliva, 2015), Quito (Carrillo et al., 2016), Santiago de Chile (Gallego et al., 2013; Rivera, 2017; Barahona et al., 2020), San José – Costa Rica (Osakwe, 2010), London (Leape, 2006; Quddus et al., 2007), Bogotá (Zhang et al., 2017), Stockholm (Simeonova et al., 2019), Taipei (Chen and Whalley, 2012), Beijing (Chen et al., 2013; Viard and Fu, 2015; Zhong et al., 2017), as well as a number of other Chinese (Lin et al., 2011; Li, 2016; Ye, 2017; Li et al., 2019) and German cities (Wolff, 2014; Gehrsitz, 2017).

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. On the other hand, our analysis considers 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.

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.

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.[2] Figure 1 shows 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.[3]

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 according to their emission level

[2] The city of Madrid has a total surface of 60,400 hectares.

[3] 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

(A, B, C, ECO and ZERO in descending order of emissions).[4] Accordingly, the city elaborated a list of exceptions that we list as follows:

(i) Residents of the MC area can enter the MC area without restrictions. If they were to buy a new car, it would need to belong to category B or cleaner to enter without restrictions. All cars of category B or cleaner can enter if they park in a public or private garage.[5]

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

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

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

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

(vi) ECO emission cars can enter to park for a maximum of two hours.

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

(viii) 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. That segment of the population cannot access the MC area at all with their own vehicles if they belong to category A, and can only access 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.

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

[4] 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 vehicles.

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

fined 90€. Our data and analysis cover this initial period up to March 16, 2019.[6] Once we have described in this section the regulation and timing of MC, we proceed with 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 credit card spending at the transaction level that we can aggregate up to pairs of zip codes for buyer-seller locations 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 indirect costs of the driving ban on consumer spending.

We collected these data not only for the MC area but for the whole metropolitan area of Madrid. Since there is no legal definition for the metropolitan area of Madrid, we define the metropolitan area of Madrid as the area that includes: (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.[7] We divide the city of Madrid into the MC area and the rest of the city. Overall, the full metropolitan area comprises 126 zip codes (56 within the city of Madrid and 70 outside). As the credit card data span from the first week of 2015 to the tenth week of 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.[8] 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

[6] This paper investigates whether the policy had a dissuasive effect during its initial phase and finds a clear and robust reduction in car traffic as a result of the introduction of MC during our period of analysis. While also interesting, our paper does not examine whether compliance increased after March 16, 2019, when fines became enforceable. Future research should pursue and answer that particular question.

[7] We check the robustness of our findings in the paper to alternative definitions.

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

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 4,152 traffic monitors across the city of Madrid. Traffic outside Madrid city is unobserved.

Traffic is measured by the number of vehicles per hour, the share of time (in %) a certain road section is occupied by a vehicle, and the share of road capacity utilized (in %). Summary statistics in Table 1 show that traffic is denser in the city center of Madrid where, on average, 28% of the road capacity is used during the week, compared to 20% outside of the city center. 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,[9] 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.[10] 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.[11] 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 both, at the station inside the MC area and at the stations outside that area, NO_2 levels are very high according to EU standards. The daily average concentration inside the MC area is 47 µg/m^3,

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

[10]Appendix Figure A.1 shows a map with locations of all pollution monitoring stations in Madrid, represented by pink circles. Blue crosses in the map indicate the location of weather stations.

[11]The aggregation of pollution and meteorological control variables could introduce measurement error. However, results on air pollution using daily observations including day-of-week fixed effects are consistent with the weekly estimations. Daily results are available from the authors upon request.

TABLE 1: Descriptive statistics on traffic and pollution levels

	Mean (1)	SD (2)	Min (3)	Max (4)	Obs (5)
Inside Madrid Central area					
Traffic (101 stations)					
Vehicles per hour	334.76	291.8	0	1,715.28	15,548
Time occupied [%]	10.65	9.73	0	98.51	15,544
Utilized capacity [%]	27.66	10.8	3.51	61.16	15,548
Pollution (1 station)					
NO_2 [$\mu g/m^3$]	47.43	12.13	26.96	95.69	216
$NO_2 > 40\,\mu g/m^3$	0.65	0.3	0	1	216
Yearly NO_2 [$\mu g/m^3$]	47.84	2.46	44.39	49.99	5
Yearly $NO_2 > 40\,\mu g/m^3$	1	0	1	1	5
Outside Madrid Central area					
Traffic (4051 stations)					
Vehicles per hour	454	509.41	0	4,354.98	604,808
Time occupied [%]	6.51	7.28	0	98.33	604,557
Utilized capacity [%]	19.92	10.84	0	99.56	603,920
Pollution (32 stations)					
NO_2 [$\mu g/m^3$]	38	16.96	3.82	133.44	6,971
$NO_2 > 40\,\mu g/m^3$	0.4	0.35	0	1	6,971
Yearly NO_2 [$\mu g/m^3$]	40.05	10.95	14.93	76.14	160
Yearly $NO_2 > 40\,\mu g/m^3$	0.47	0.5	0	1	160

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

while it is $38\,\mu g/m^3$ 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. Moreover, other stations outside the city center also violate the threshold. This happens in 47% 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 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, 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

TABLE 2: Descriptive statistics on weather conditions

	Mean (1)	SD (2)	Min (3)	Max (4)	Obs (5)
Temperature [°C]	15.68	7.69	1.23	30.87	7,187
Precipitation [0.1mm]	10.69	18.21	0	158.29	7,187
Cloud cover [okta]	3.42	1.77	0	7.71	7,187
Sunshine [h]	8.19	2.97	0.97	13.91	7,187
Pressure [hPa]	1,017.38	6.2	994.9	1,035.49	7,187
Humidity [%]	57.96	15.62	22.29	92.86	7,187
Wind speed [0.1 m/s]	22.56	10.36	1.71	80.14	7,187
$0° \leq$ Wind direction $< 45°$	0.22	0.22	0	1	7,187
$45° \leq$ Wind direction $< 90°$	0.14	0.18	0	0.86	7,187
$90° \leq$ Wind direction $< 135°$	0.09	0.13	0	0.86	7,187
$135° \leq$ Wind direction $< 180°$	0.05	0.1	0	0.57	7,187
$180° \leq$ Wind direction $< 225°$	0.12	0.16	0	1	7,187
$225° \leq$ Wind direction $< 270°$	0.2	0.2	0	1	7,187
$270° \leq$ Wind direction $< 315°$	0.11	0.15	0	1	7,187
$315° \leq$ Wind direction $< 360°$	0.07	0.12	0	1	7,187

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

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.[12] In our data, temperature is measured in degrees Celsius, precipitation in tenths of millimeters, cloud cover in okta,[13] 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

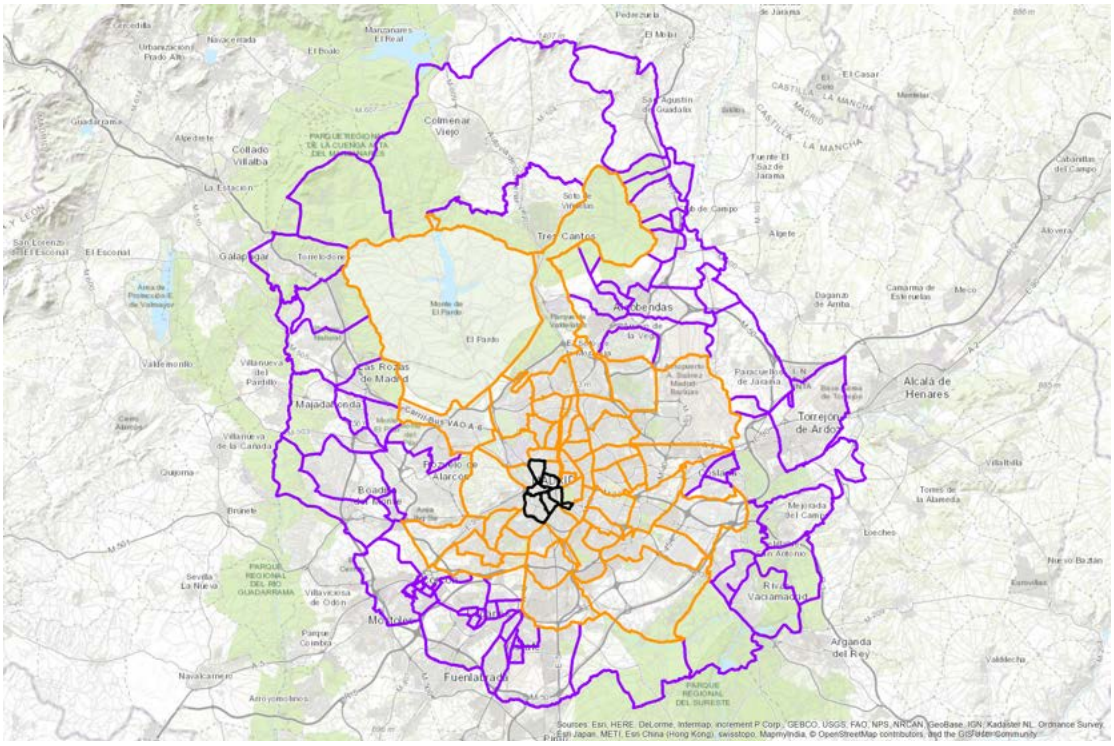
The final database contains data at the credit card transaction-level from a large European bank.[14] The original data set is unique in that it details the date

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

[13] 0 okta indicates no clouds and 8 okta full cloud cover.

[14] 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 the metropolitan area of Madrid that are made, either online or offline, 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.

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.

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).[15] Due to our confidentiality agreement with the bank providing the data, we aggregate transaction information at the weekly buyer-seller zip code level from the first week of 2015 to the tenth week of 2019. Figure 2 shows all 126 zip codes in Madrid. Six zip codes belong to the MC area, 50 zip codes to the rest of the city of Madrid, and 70 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.

Table 3 presents summary statistics for the main variables of our analysis aggregated at the weekly seller-buyer zip codes level. The average value of "trade flows" between zip codes is 2,087€ coming from on average 54 transactions. The average value of a transaction is 29€. A unique feature of our data is that we

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

Table 3: Descriptive statistics on sales

	Mean (1)	SD (2)	Min (3)	Max (4)
Total value	2,087.29	9,644.52	0	606,469
B&M value	1,954.69	9,488.51	0	606,469
Online value	132.59	633.51	0	126,363
Total transactions	53.87	268.20	0	16,696
B&M transactions	51.13	264.92	0	16,605
Online transactions	2.73	14.08	0	701
Total transaction value	28.73	39.44	0.09	9,227.47
B&M transaction value	27.59	38.74	0.09	9,227.47
Online transaction value	16.18	72.46	0.12	31,539.1
Share of obs with 0 total value	0.22			
Share of obs with 0 B&M value	0.23			
Share of obs with 0 online value	0.71			

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

are able to separate transactions into two types: brick-and-mortar transactions (B&M in the tables) and online transactions. This is an important feature because it allows us to test the transportation cost mechanism given that transportation costs increase for brick-and-mortar transactions and 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 a specific treated zip code 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 majority of flows are from 51 brick-and-mortar transactions with a total value of 1,955€, on average. The total value of online transactions is on average 132€, coming from three online transactions. 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. 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

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.

percentage increases for zip codes in the rest of the city of Madrid and outside the city (90% and 95%). 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 the 50 zip codes in Madrid city and only 0.4% to each of the 70 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. 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 living in different areas of Madrid spend within their local zip code. 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.

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

Y_{swy} stands for the traffic or pollution outcome of interest at the traffic or air quality monitor station s, week w, and 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.[16] For example, these would control for the

[16]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.

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 by β, while controlling for possible confounding factors.

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 also 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.[17]

4.2 Results

Table 5 presents the results of estimating Equation (1) for the three measures of traffic, in levels and logs, with standard errors clustered at the station level. We find large effects of MC on traffic. The average number of cars dropped by 48.5 (column 1), or 14.7 percent (column 4). MC reduced the frequency of road segment usage by cars by 1.9 percentage points (column 2), or 17.8 percent (column 5). A decrease in these two measures implies that roads are used less, in fact, road capacity utilized under MC decreased by 5.7 percentage points (column 3), or 22.8 percent (column 6). These estimates are not only statistically significant at the

[17] 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.

Table 5: Effects on traffic levels

	Vehicles per hour (1)	Time occupied [%] (2)	Utilized capacity [%] (3)	Log Vehicles per hour (4)	Log Time occupied (5)	Log Utilized capacity (6)
Madrid Central	−48.500***	−1.936**	−5.679***	−0.147***	−0.178***	−0.228***
	(12.130)	(0.850)	(0.776)	(0.025)	(0.050)	(0.038)
Location-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.	456.300	6.571	20.190	5.648	1.493	2.905
N×T	597,221	596,895	596.328	597,031	592,874	571.518
N	3948	3948	3948	3948	3927	3823

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 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.

1% level while clustering at the monitoring station level, but also are economically significant magnitudes.

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 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 one if station s is inside a 1.5 km buffer around the MC area in a year-week in which MC is enforced.[18] Appendix Table C.1 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 not accounting for positive spillover effects leads to an underestimation of the absolute effect on traffic inside the MC area.

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 16 percent in NO_2 in the restricted area due to the introduction of MC. Defining the three closest stations inside the 1.5 km buffer around the MC area (see Appendix Figure A.1) 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. This

[18]Results are robust to defining alternative buffers around the MC area. These are available upon request.

Table 6: Effects on NO_2 levels

	Log NO_2			$NO_2 > 40$		
	(1)	(2)	(3)	(4)	(5)	(6)
Madrid Central	−0.162***	−0.163***	−0.136***	−0.121***	−0.122***	−0.111***
	(0.017)	(0.018)	(0.038)	(0.015)	(0.016)	(0.031)
Surroundings		−0.008	0.018		−0.015	−0.004
		(0.032)	(0.046)		(0.029)	(0.030)
City of Madrid			0.036			0.015
			(0.042)			(0.034)
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.	3.545	3.545	3.545	0.408	0.408	0.408
N×T	7187	7187	7187	7187	7187	7187
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.

result could be due to the fact that the reduction of traffic in the surroundings is not strong enough or because the composition of cars outside the regulated area is unaffected. We repeat the same exercise in column 3, considering spillovers to any station within the city of Madrid. The effect on the MC area is now slightly smaller in magnitude, 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 of a week in which NO_2 levels exceed $40\,\mu g/m^3$. Our findings here are consistent with those in columns 1 to 3, suggesting a decrease of 12 percentage points in the days of a week in which NO_2 levels exceed $40\,\mu g/m^3$. This represents a 25% reduction relative to the sample mean. These results are confirmed by Pseudo-Maximum Likelihood Poisson regressions in Appendix Table C.2, where the outcome is the number of days in a given week in which the limit value was exceeded.

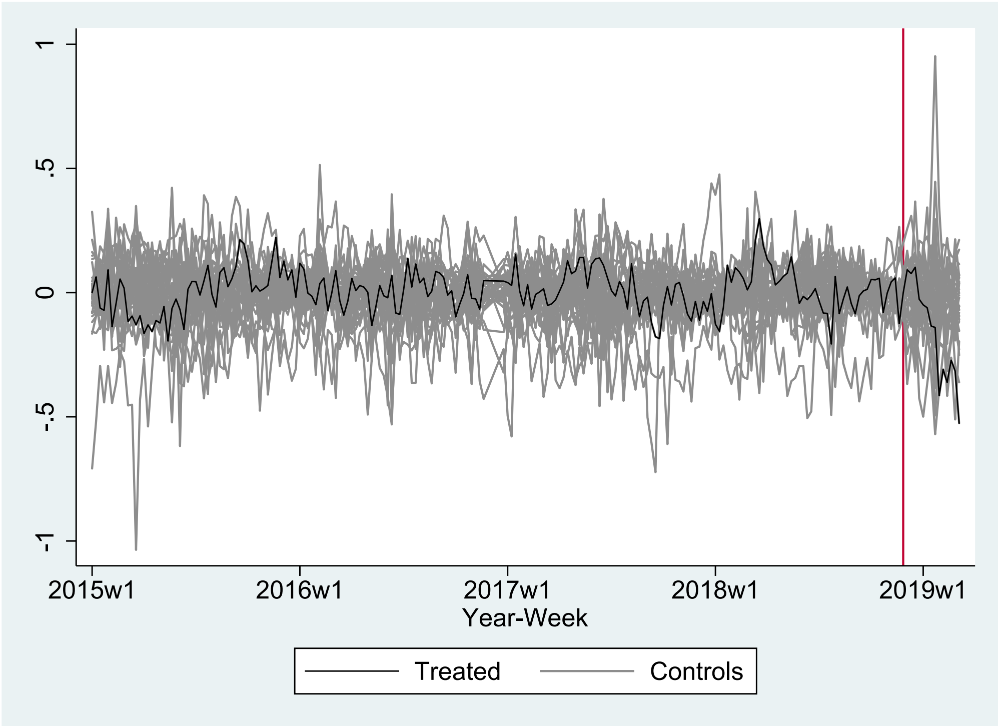
4.3 Robustness checks

Our results appear to remain unchanged both qualitatively and quantitatively when including station-specific trends (Appendix Table C.3). In a separate specification, we also include the air quality monitoring stations located in Barcelona as a control group and find that results remain mostly unchanged, except for a small reduction in the impact on the share of days exceeding 40 µg/m^3 (Appendix Table C.4).

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 0.88.

Figure 3 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 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.

FIGURE 3: 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 a actual measurement and a prediction based on controls stations. The vertical red line indicates the introduction of Madrid Central.

5 The effect of Madrid Central on consumption spending

The results in Section 3 indicate that MC achieved its goal of reducing car traffic and pollution levels in the city center of Madrid. However, this may come at the cost of distorting citizens' habits and market outcomes. One of the most salient and controversial dimensions of these distortions is the possible impact that MC may have had on consumption 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 actually 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 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 dyad 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.[19]

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 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

[19] 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.

(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.[20] Moreover, 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 one if i is a buyer-zip code outside the MC area,

[20] 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 of MC area in establishments inside the MC area. In turn, if the reduction of consumption in 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 if the number of zip codes is large enough. We have 126 zip codes, which should make our case comparable to the usual International Trade framework modeling trade across countries.

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. Note this dummy is aimed to capture increases in transportation cost between a zip code pair triggered by the introduction of MC, and that 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.[21] 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 MC area.

The coefficient of interest, β, identifies the partial equilibrium effect of the increased transportation costs due to Madrid Central. 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 in all seller-zip codes, both inside and outside of the MC area (Larch and Yotov, 2016; Piermartini and Yotov, 2016).[22] 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}.[23]

[21]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.

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

[23]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 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. To study whether there are changes in the attractiveness of the MC area, we show diff-in-diff results in Table 10.

5.2 Results

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.[24]

We estimate β from specification (2) and show results of the triple difference estimation in Table 7. In columns 1 and 2, we use total transaction revenue as the dependent variable and find with a statistically insignificant decrease of 3 percent in spending in the MC area by affected consumers. Columns 3 to 6 examine the impact of MC on brick-and-mortar and online transactions separately. While MC decreases brick-and-mortar spending between 4.7 and 8.9 percent, it increases online spending between 9.4 and 12.1 percent. All four columns show statistically significant findings. Therefore, 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 consumption spending from brick-and-mortar to online transactions. Note that we show in Appendix Table D.1 that mean transaction values for all, brick-and-mortar, and online transactions did not statistically change due to the introduction of MC. Additionally, Appendix Table D.2 regresses the share of online revenue and the share of online transactions per buyer-seller zip codes dyad and finds results consistent with those in Table 7, as well as no statistical change in the relative size of brick-and-mortar to online transaction values.

Estimates in Table 7 correspond to the partial equilibrium impact of Madrid Central, 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 9 percent decrease in brick-and-mortar consumption in the MC area by affected consumers 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 9 percent. Because only five out of 126 zip codes were directly affected by Madrid Central, 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

[24] 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).

Table 7: Baseline Results

	Total		B&M		Online	
	Rev (1)	Trans (2)	Rev (3)	Trans (4)	Rev (5)	Trans (6)
Treatment	−0.039	−0.029	−0.090**	−0.047*	0.121**	0.094**
	(0.038)	(0.024)	(0.040)	(0.025)	(0.061)	(0.044)
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	3,460,968	3,460,968	3,460,968	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 pair level. The dependent variable is log of revenue and log of number of transactions for all transactions, brick-and-mortar and 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.

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.

An interesting departure from specification (2) is one where we split the dummy of interest, MC_{ijwy}, into two: one for those buyers living in zip codes within the limits of the city of Madrid (and outside the MC area), and one for those zip codes located outside the city of Madrid and still inside the metropolitan area of Madrid. This alternative specification accounts for potential differences in the set of available transportation options to the center of the city of Madrid. 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 at low costs by 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 is less convenient. In Appendix Table D.3 we use estimates on travel times from 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.

The results of this exercise are reported in Table 8. Columns 1 and 2 show that MC did not have a statistically significant impact on total revenue or the number

TABLE 8: Heterogeneous effects

	Total		B&M		Online	
	Rev (1)	Trans (2)	Rev (3)	Trans (4)	Rev (5)	Trans (6)
Zip codes city	-0.0376	-0.0299	-0.0804*	-0.0399	0.049	0.0763*
	(0.0394)	(0.0251)	(0.0418)	(0.0261)	(0.0629)	(0.0454)
Zip codes out of city	-0.0391	-0.0285	-0.0959**	-0.0524**	0.172***	0.107**
	(0.041)	(0.0254)	(0.0441)	(0.0265)	(0.064)	(0.0451)
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
p-val equal effects	0.956	0.921	0.581	0.4	0.00155	0.0699
Observations	3,460,968	3,460,968	3,460,968	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 pair level. The dependent variable is log of revenue and log of number of transactions for the full sample, brick-and-mortar and online transactions at the seller-zip code by buyer-zip code level in a given week. The variable Zip codes city takes value one when (1) the 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 but within the city of Madrid, and 0 otherwise. The variable Zip codes out of city is defined in the same way but for buyer-zip codes outside the city of Madrid.

of transactions, neither from Madrid city zip codes nor from zip codes outside of Madrid. These findings are consistent with those shown in Table 7.

Next, we examine spatial heterogeneity of the impact of MC on brick-and-mortar revenues and number of transactions. The results in columns 3 and 4 show that brick-and-mortar revenues and transactions decrease across the board. The magnitude of the decrease in revenues and transactions is larger for buyer-zip codes outside the city of Madrid, although we cannot statistically reject the hypothesis that they are the same. Interestingly, we find opposite findings regarding online transactions. Columns 5 and 6 show that online revenues and transactions increased across the board. The magnitude of the increase is larger for revenues and transactions in buyer-zip codes outside the city of Madrid, where the increase in transportation cost to the MC area is likely to be largest. Moreover, we can reject the null hypothesis that the effects on online transactions are equal for buyer-zip codes inside and outside the city of Madrid.[25] Again, this indicates a substitution between brick-and-mortar and online consumption due to the increase in transportation costs for residents living outside the MC area.

We have made two important observations. First, transportation costs matter as MC affects consumer behavior. The increase in transportation decreases con-

[25]Note that these findings also provide an alternative way of testing the impact of MC on online consumption levels of consumers living outside the city of Madrid by using as a control group online consumption levels of consumers inside the city of Madrid and outside the MC area.

Table 9: Gravity

	Total revenue (1)	B&M revenue (2)	Online revenue (3)	Share online revenue (4)
Log distance between zip codes	-1.722***	-1.767***	-0.608***	2.080***
	(0.0196)	(0.0196)	(0.0157)	(0.0792)
Buyer-week-year FE	Yes	Yes	Yes	Yes
Seller-week-year FE	Yes	Yes	Yes	Yes
Observations	3,460,968	3,460,968	3,460,968	3,460,968

Notes: Dependent variable: Log of revenue for all transactions, B&M and online transactions separately and percentage share of online revenue. *** denotes significance at 1%, ** at 5%, and * at 10%. Standard errors are clustered at the buyer-seller pair level. The dependent variable is the log of revenue for all transactions, brick-and-mortar and online transactions at the seller-zip code by buyer-zip code level in a given week (cols. 1-3), and the percentage share of online revenue for that seller-buyer-week triple (col. 4). The independent variable is the log of distance measured in km between the centroid of the seller-zip code and the centroid of the buyer-zip code. In all columns, we control for seller-week-year specific FE and buyer-week-year specific FE.

sumer spending in brick-and-mortar establishments. Second, when transportation costs increase, there is a switch from brick-and-mortar to online spending. We examine these general mechanisms in Table 9 and find that, indeed, consumption exhibits gravity. Spending decreases with distance for both brick-and-mortar and online consumption. But relatively, the impact of distance is greater for brick-and-mortar consumption such that the share of online purchases increases with distance. This is important for two distinct purposes. On the one hand, we show that transportation costs within a city matter. On the other hand, we confirm the need to control for seller-buyer zip codes pair fixed effects to clear problems of endogeneity. The existence of gravity implies that those buyers located furthest away from the MC area were buying little in the MC area to begin with. Consequently, the introduction of MC increased transportation costs of those buyers located further away from the MC area to a greater extent. This means that we must include buyer-seller zip code fixed effects to avoid negative bias in the estimation of the effect of MC on consumption spending.[26]

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 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 do not decrease their

[26] Appendix Table D.4 replicates Table 7 without buyer-seller-zip code fixed effects and shows the importance of controlling for the underlying variation across zip code pairs.

TABLE 10: Seller-zip code sales

	Total		B&M		Online	
	Rev	Trans	Rev	Trans	Rev	Trans
	(1)	(2)	(3)	(4)	(5)	(6)
Madrid Central	0.054	0.060**	0.059	0.044	−0.026	0.068
	(0.044)	(0.027)	(0.047)	(0.028)	(0.142)	(0.163)
Week-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Seller FE	Yes	Yes	Yes	Yes	Yes	Yes
Seller trends	Yes	Yes	Yes	Yes	Yes	Yes
Observations	27,594	27,594	27,594	27,594	27,594	27,594

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Standard errors are clustered at the seller-zip code level. The dependent variable is the log of revenue for total transactions, brick-and-mortar and online transactions at the seller-zip code level in a given week. The variable Madrid Central takes value 1 when a seller-zip code is within the MC area and the MC regulations are in place, and 0 otherwise.

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. We can examine this pathway in a simple difference-in-difference specification, comparing sales inside and outside the regulated area. Nevertheless, such a 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.

Aggregating Equation (2) to the seller-zip code level, we obtain the following difference-in-differences specification.

$$Y_{jwy} = \alpha_{wy} + \gamma_j + \theta_j t + \beta MC_{jwy} + u_{jwy} \tag{3}$$

The outcome Y_{jwy} measures how much sellers in zip code j sell in week w of year y. The variable MC_{jwy} is a dummy that takes value one if seller j is in a zip code inside the MC area and in a week-year in which MC is in effect. The parameter β is the coefficient of interest as it measures the effect of MC on sales of establishments within the MC area once the policy is in effect. The parameter α_{wy} is the week-year fixed effect, γ_j is the seller-zip code fixed effect, and $\theta_j t$ is a seller-zip code specific time trend. Therefore, the identification of the effect occurs conditional on the seller-zip code specific level and its trend. Finally, u_{jwy} is the usual error term.

Columns 1 and 2 of Table 10 show an insignificant increase of 5 percent in sales and a 6 percent increase in transactions, which is significant at the 5% level. Note that this is a rather convenient result for policy makers confronted with opposition by local business in the MC area: MC reduced traffic congestion and air pollution with no statistically significant impact on economic activity. In columns 3 to 6, we split the revenue and number of transactions at the seller-zip code level into brick-and-mortar and online transactions but find no significant effects. Together with the previous results, this could suggest a potential increase of the potential attractiveness of the MC area.[27]

5.3 Robustness checks

A concern with our triple difference specification is the potential existence of different pretrends. Therefore, different trends in the propensity of different buyer-zip codes to buy in each seller-zip code could invalidate the results in Table 7. To address this concern, in Table 11, we present results from a falsification test. We define an additional falsification variable which assumes that the introduction of MC took place approximately one month and a half before it actually did (it was introduced in week 49 of 2018 and we assume it was introduced in week 43).[28] We would expect to observe some effect if differential trends play a role. This is not the case. This result also allows us to rule out the existence of potential anticipatory effects that might induce consumers to bring forward consumption in MC area as a result of the imminent increase in transaction costs.

Another potential concern arises from the incidence of zeros in trade flows between some zip code pairs. So far, we have adopted the traditional solution of adding one to the dependent variable of interest to avoid dropping observations once we take logs. Table 12 shows an alternative approach 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). Column 1 shows very similar results for the effects on brick-and-mortar revenues. Column 2 finds a positive impact of MC on online revenues. Column 3 shows that the impact on total revenues is smaller in magnitude and statistically insignificant. This set of results is consistent with the main findings of the paper in Table 7.

[27] Appendix Table D.5 shows that excluding zip code-specific time trends yields no qualitatively different results except for online sales.

[28] The findings in Table 11 are robust to using other placebo starting dates such as 4 or 8 weeks before week 49 of 2018. These results are available upon request.

Table 11: Falsification Test

	B&M (1)	Online (2)	Total (3)
Treatment	-0.0895**	0.121**	-0.0385
	(0.0409)	(0.0606)	(0.038)
Falsification	0.00509	0.000127	0.0437
	(0.048)	(0.102)	(0.0482)
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 pair level. The dependent variable is log of revenue and log of number of transactions for the full sample, brick-and-mortar and online transactions 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 Falsification is defined in the same way but assumes that MC was introduced six weeks earlier.

A third set of robustness checks is concerned with the fact that differences in transportation costs may have changed differently across zip codes at the same physical distance. Table 13 presents further evidence consistent with the fact that an increase in transportation costs drives the substitution between brick-and-mortar and online consumption. 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 between those above and below the median of the increase in travel time. We observe that, although the decrease in brick-and-mortar sales is not statistically significant for zip codes with high and low travel time increments, those zip codes with a high increase in travel times drive the increase in online purchases.

We also test a number of alternative specifications. Appendix Table D.6 shows results of dividing buyer zip codes into two groups, closer and farther than 6 km from the MC area, as well as results from dropping observations more than 15 km away from the MC area. Appendix Table D.7 includes specifications where buyer-zip codes are weighed by their volume of sales. It also includes other specifications with week-year fixed effects interacted with the distance between each zip code and the center of the MC area to control for changes over time in spending behavior which correlate with geographic consumer location. Our results are qualitatively robust to these alternative specifications.

Table 12: Poisson Pseudo Maximum Likelihood

	B&M (1)	Online (2)	Total (3)
Treatment	-0.0797**	0.0668***	-0.0286
	(0.031)	(0.0246)	(0.0299)
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 pair level. The dependent variable is revenue for brick-and-mortar, online and total transactions 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. Estimation by Poisson Maximum Likelihood.

Table 13: Heterogeneity by Increase in Travel Time

	B&M (1)	Online (2)	Total (3)
Zip codes low increase	-0.0915**	0.0906	-0.0546
	(0.0418)	(0.0635)	(0.0387)
Zip codes high increase	-0.0876*	0.148**	-0.0239
	(0.0448)	(0.0641)	(0.042)
Buyer-week-year FE	Yes	Yes	Yes
Seller-week-year FE	Yes	Yes	Yes
Buyer-seller-week FE	Yes	Yes	Yes
p-val equal effects	0.893	0.151	0.276
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 pair level. The dependent variable is level of revenue for brick-and-mortar, online and total transactions at the seller-zip code by buyer-zip code level in a given week. The variable Zip codes low increase takes value one when (1) the seller-zip code is within the MC area and the MC regulations are in place and (2) the buyer-zip code faces a low travel time increase, and 0 otherwise. The variable Zip codes high increase takes value one when (1) the seller-zip code is within the MC area and the MC regulations are in place and (2) the buyer-zip code faces a high travel cost increase, and 0 otherwise.

6 Conclusion

This paper analyzes the benefits and costs of the introduction of constraints to vehicle circulation in the center of Madrid. By 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.

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 that there was not a statistically significant impact on total spending and number of transactions due to the policy. Yet, when we separate brick-and-mortar and online transactions, we find that 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 shows that when consumers face larger transportation costs, they switch from brick-and-mortar to online consumption spending.

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 could compensate 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 that it 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 evidence 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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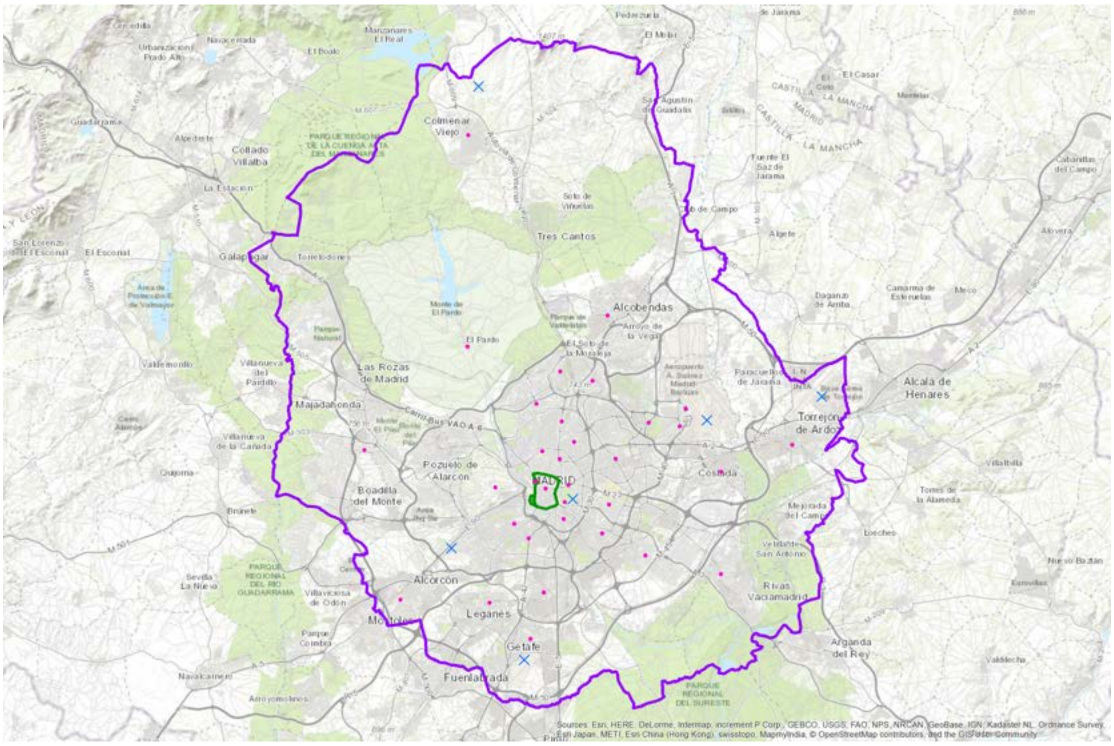
A Maps

Figure A.1 displays the locations of the 33 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.

FIGURE A.1: Map of stations



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]	15.63	7.74	3.39	30.87	616,297
Precipitation [0.1mm]	10.43	17.78	0	131.43	616,297
Cloud cover [okta]	3.45	1.76	0	7.57	616,297
Sunshine [h]	8.2	2.92	1.13	13.41	616,297
Pressure [hPa]	1017.25	6.09	998.21	1035.54	616,297
Humidity [%]	58.29	14.54	26.29	90.29	616,297
Wind speed [0.1 m/s]	19.73	8.46	0.43	75.43	616,297
$0° \leq$ Wind direction $< 45°$	0.19	0.19	0	1	616,297
$45° \leq$ Wind direction $< 90°$	0.17	0.18	0	0.71	616,297
$90° \leq$ Wind direction $< 135°$	0.1	0.14	0	0.86	616,297
$135° \leq$ Wind direction $< 180°$	0.05	0.1	0	0.57	616,297
$180° \leq$ Wind direction $< 225°$	0.1	0.14	0	0.86	616,297
$225° \leq$ Wind direction $< 270°$	0.22	0.21	0	1	616,297
$270° \leq$ Wind direction $< 315°$	0.12	0.15	0	0.86	616,297
$315° \leq$ Wind direction $< 360°$	0.06	0.1	0	0.86	616,297

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 including a dummy for whether the traffic monitoring station is located in the surroundings of the MC area.

Table C.1: Effects on traffic levels: Spillovers

	Vehicles per hour (1)	Time occupied [%] (2)	Utilized capacity [%] (3)	Log Vehicles per hour (4)	Log Time occupied (5)	Log Utilized capacity (6)
Madrid Central	-52.63***	-1.987**	-6.043***	-0.153***	-0.179***	-0.241***
	(12.14)	(0.85)	(0.777)	(0.0247)	(0.0496)	(0.0379)
Surroundings	-25.51***	-0.318*	-2.248***	-0.0375***	-0.00897	-0.0899***
	(3.741)	(0.171)	(0.199)	(0.00623)	(0.0171)	(0.0109)
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.	456.3	6.571	20.19	5.648	1.493	2.905
N×T	597,221	596,895	596,328	597,031	592,874	571,518
N	3,948	3,948	3,948	3,948	3,927	3,823

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.

Table C.2 replicates Table 6 with Poisson regressions, counting the number of days on which NO_2 exceeded the limit value of 40 µg/m^3.

TABLE C.2: Effects on Air Pollution Levels: Poisson Regressions

	$NO_2 > 40$		
	(4)	(5)	(6)
Madrid Central	-0.178***	-0.182***	-0.158***
	(0.0223)	(0.0248)	(0.0571)
Surroundings		-0.0255	-0.00185
		(0.0461)	(0.0683)
City of Madrid			0.0308
			(0.06)
Station-Week FE	Yes	Yes	Yes
Year-Week FE	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes
Mean dep. var.	0.46	0.46	0.46
N×T	6,381	6,381	6,381
N	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. Estimation is done by Poisson regression.

Table C.3 replicates the exercise in Table 6 with station-specific trends.

Table C.3: Regression of NO_2 levels with station-specific trends

	Log NO_2			$NO_2 > 40$		
	(1)	(2)	(3)	(4)	(5)	(6)
Madrid Central	-0.158***	-0.157***	-0.146***	-0.135***	-0.136***	-0.130***
	(0.0157)	(0.0173)	(0.0398)	(0.0165)	(0.0168)	(0.0301)
Surroundings		0.0149	0.0254		-0.00735	-0.00172
		(0.0299)	(0.0467)		(0.0618)	(0.066)
City of Madrid			0.0146			0.0078
			(0.044)			(0.0318)
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.	3.545	3.545	3.545	0.408	0.408	0.408
N×T	7,187	7,187	7,187	7,187	7,187	7,187
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.

Table C.4 includes pollution in Barcelona in the control group.

TABLE C.4: Regression of NO_2 levels including Barcelona

	Log NO_2			$NO_2 > 40$		
	(1)	(2)	(3)	(4)	(5)	(6)
Madrid Central	-0.157***	-0.147***	-0.167***	-0.103***	-0.0847***	-0.0723***
	(0.0154)	(0.023)	(0.0185)	(0.0127)	(0.0185)	(0.0181)
Surroundings		0.0182	-0.00232		0.0339	0.0464*
		(0.0315)	(0.0278)		(0.0256)	(0.0264)
City of Madrid			-0.0391			0.0239
			(0.0471)			(0.0398)
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.	3.563	3.563	3.563	0.418	0.418	0.418
N×T	8,708	8,708	8,708	8,708	8,708	8,708
N	40	40	40	40	40	40

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 presents results of the impact of MC on mean transaction values. Using specification (2), now we use as the dependent variable the mean value of transactions for all transactions in column one, for brick-and-mortar transactions in column 2, and for online transactions in column 3. There are no significant changes in mean transaction values for any of the three categories.

Table D.1: Effects on Transaction Values

	Total (1)	B&M (3)	Online (5)
Treatment	-0.00942 (0.0267)	-0.0423 (0.0288)	0.0265 (0.0461)
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: Log of mean transaction value for all transactions, B&M and online transactions. *** denotes significance at 1%, ** at 5%, and * at 10%. Standard errors are clustered at the buyer-seller pair level. The dependent variable is log of the mean transaction value (calculated as the ratio between total revenue over number of transactions) for all transactions, brick-and-mortar and online transactions at the seller-zip code by buyer-zip code level in a given week.

Table D.2 replicates the specification in Table 7 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.2: Online Shares

	Share online revenue	Share online transactions	Ratio transaction values
	(1)	(2)	(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 ratios 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 Table D.3 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.3 shows that the time loss due to public transport usage is 12 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.3: Changes in Travel Time

	(1)
Zip codes out of city	12.40***
	(2.46)
Observations	126

Notes: Dependent variable: Changes in travel time to 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.

Table D.4 replicates results of Table 7 without buyer-seller-zip code pair fixed effects and displays the importance of controlling for the underlying variation across zip code pairs.

TABLE D.4: No buyer-seller pair specific FE

	Total		B&M		Online	
	Rev	Trans	Rev	Trans	Rev	Trans
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	-1.835***	-1.909***	-2.007***	-1.994***	-1.360***	-0.779***
	(0.158)	(0.161)	(0.163)	(0.163)	(0.133)	(0.0932)
Buyer-week-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Seller-week-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Buyer-seller-week FE	No	No	No	No	No	No
Observations	3,460,968	3,460,968	3,460,968	3,460,968	3,460,968	3,460,968

Notes: Dependent variable: Log of revenue and log of number of transactions for all transactions, B&M and online transactions. *** denotes significance at 1%, ** at 5%, and * at 10%. Standard errors are clustered at the buyer-seller pair level. The dependent variable is log of revenue and log of number of transactions for all transactions, brick-and-mortar and online transactions 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 traffic restriction is in place, and (2) the buyer-zip code is outside the MC area, and 0 otherwise. In all columns we control for buyer-week-year specific FE, and seller-week-year specific FE.

Table D.5 shows results of alternative difference-in-differences specifications to those in Table 10 with sales aggregated at the seller-zip code level without time trends for each seller-zip code.

Table D.5: Seller-zip code sales without trends

	Total		B&M		Online	
	Rev	Trans	Rev	Trans	Rev	Trans
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	-0.0987	0.00298	-0.123	0.0302	-0.284**	-0.419**
	(0.148)	(0.0604)	(0.160)	(0.0606)	(0.118)	(0.0786)
Week-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Seller FE	Yes	Yes	Yes	Yes	Yes	Yes
Seller trends	No	No	No	No	No	No
Observations	27,594	27,594	27,594	27,594	27,594	27,594

Notes: Dependent variable: Log revenue and log transactions for all, B&M and online transactions. *** denotes significance at 1%, ** at 5%, and * at 10%. Standard errors are clustered at the seller-zip code level. The dependent variable is the log of revenue for brick-and-mortar, online and total transactions at the seller-zip code level in a given week. The variable Treatment takes value 1 when a seller-zip code is within the MC area and the traffic restriction is in place. In all columns we control for week specific FE, and seller zip code FE. In columns 2, 4, and 6 we further include seller-zip code specific trends and trends squared.

Table D.6 presents robustness checks in which we change the sample definition and the definition of strongly affected and mildly affected zip codes. In columns 1 to 3, we consider that those zip codes mildly affected by MC are zip codes within six km of the MC area. We consider a zip code is within six km of the MC area if the centroid of the zip code is within six kms of Puerta del Sol (a square that represents the centroid of the MC area). We use the same criterion to determine which zip codes are within 15 km of the MC area. The results are qualitatively unaffected by this change in definition. In columns 4 to 6, we reduce the sample to only those zip codes within 15 km of the MC area, and consider those within six km to be mildly affected. Again, our heterogeneity results are qualitatively similar to those in Table 8.

TABLE D.6: Robustness Results I

	All Sample			Zip codes within 15km		
	B&M	Online	Total	B&M	Online	Total
	(1)	(2)	(3)	(4)	(5)	(6)
Zip codes < six km	-0.0719*	0.0185	-0.0463	-0.0612	0.04	-0.0312
	(0.0436)	(0.0668)	(0.0407)	(0.0423)	(0.071)	(0.0398)
Zip codes > six km	-0.0948**	0.152**	-0.0361	-0.0939**	0.147**	-0.0387
	(0.0422)	(0.062)	(0.0393)	(0.0416)	(0.0698)	(0.0395)
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
p-val equal effects	0.413	0.0015	0.707	0.259	0.0291	0.792
Observations	3,460,968	3,460,968	3,460,968	1,575,050	1,575,050	1,575,050

Notes: Dependent variable: Log of revenue. *** denotes significance at 1%, ** at 5%, and * at 10%. Standard errors are clustered at the buyer-seller pair level. The dependent variable is log of revenue for brick-and-mortar, online and total transactions at the seller-zip code by buyer-zip code level in a given week. The variable Zip codes < six km takes tvalue 1 when (1) the 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 but within six km of the MC area, and 0 otherwise. The variable Zip codes > six km takes value 1 when (1) the seller-zip code is within the MC area and the MC regulations are in place and (2) the buyer-zip code is further than six kms from the MC area, and 0 otherwise. In all columns, we control for buyer-week-year specific FE, seller-week-year specific FE and buyer by seller by week of the year FE.

Table D.7 presents further robustness checks. In columns 1 to 3 of Table D.7, we weight information from each of the buyer-zip codes by the average volume of total sales of the given zip code during the year 2015. The estimates remain similar in magnitude. The main difference is that now the decrease in total revenue from buyer-zip codes outside the city of Madrid becomes significant. The propensity of consumers to buy in zip codes located further away might change over time. For this reason, columns 4 to 6 in Table D.7 introduce a week-year fixed effect interacted with the distance between the buyer-zip code and the seller-zip code. This set of interactions controls for a potential increase in propensity to buy in zip codes that are further away from the local zip code. We can see how results are robust to this and, if anything, are larger in magnitude and more significant.

Table D.7: Robustness Results II

	Weights			Extra Controls		
	B&M	Online	Total	B&M	Online	Total
	(1)	(2)	(3)	(4)	(5)	(6)
Zip codes city	-0.0788**	0.0413	-0.049	-0.0831**	0.105*	-0.0442
	(0.0338)	(0.0647)	(0.0322)	(0.0419)	(0.0628)	(0.0395)
Zip codes out of city	-0.138***	0.186***	-0.0847**	-0.101**	0.284***	-0.0525
	(0.0357)	(0.0694)	(0.0337)	(0.0444)	(0.0639)	(0.0414)
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
Week-year FE × zip code distance	No	No	No	Yes	Yes	Yes
p-val equal effects	0.0124	0.000946	0.115	0.519	0.00000444	0.766
Observations	3,460,968	3,460,968	3,460,968	3,460,968	3,460,968	3,460,968

Notes: Dependent variable: Log of revenue. *** denotes significance at 1%, ** at 5%, and * at 10%. Standard errors are clustered at the buyer-seller pair level.