Market competition and the adoption of clean technology: evidence from the taxi industry*

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PRELIMINARY DRAFT—PLEASE DO NOT CIRCULATE

Abstract

This paper studies the impact of the intensity of market competition on firms' willingness to adopt green technologies —which has become particularly relevant in the light of the debate on whether competition policies should be relaxed to achieve certain environmental targets. We exploit the staggered rollout of different rail-hailing platforms (most notably, Uber) across different metropolitan areas in Spain as a natural experiment that provides time and city-specific exogenous variation in the intensity of competition to study the impact on taxi drivers' decisions to purchase "green" or "dirty" vehicles. We show that the entry of these platforms significantly increased the takeout of green vehicles among professional drivers in incumbent (dominant) conventional taxi companies, and decreased that of dirty vehicles. The exact opposite effect is observed in the cities where these platforms were extremely unlikely to enter. Back of the envelope calculations suggest that the entry of Uber is associated with an extra green vehicle purchase in every four among taxi drivers, resulting in a substantial drop in the level of emissions from the taxi fleet —still mostly dominated diesel vehicles.

Keywords: Technological change; Green technology adoption; Market competition; Diffusion of technology; Environmental externalities.

JEL Classification Numbers: D22, K32, L20, O30, O33, Q55, R11.

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1 Introduction

The question on the role of the intensity of competition and market structure in firms' willingness to innovate and in the diffusion of technology has sparked an intense debate among economists and policy-makers that dates back to the 1940s. Two major conflicting theories find their roots in the pioneer contributions on this topic. Namely, while Shumpeter (1942) argues that monopolies favor innovation and, consequently, "market power is the price that society must pay for rapid technological progress", Arrow (1972) claims that competitive pressure is the main driving force of innovation and, eventually, of the adoption of new technologies. More recent contributions, such as Aghion et al. (2005), provide some middle ground between these two conflicting theories.

However, this question has been asked with increasing force in the past few years. This is because the diffusion of innovation and technological change is critical not only for economic growth and productivity, but they have also become key towards the fighting of environmental externalities such as greenhouse gas emissions, pollution, and climate change. To facilitate the adoption of new environmentally-friendly technologies, many countries have implemented regulatory measures that make it less attractive to use highly pollutant technologies —for instance, through fiscal tools (e.g. environmental taxes) or artificial markets that allow firms to internalize the cost of emissions (e.g. carbon markets and emissions trading schemes)—; and that incentivize the use cleaner ones —for instance, through subsidies.

Unfortunately, it is well-acknowledged that governments are usually not effective in inducing the adoption of new clean technologies —Bénabou and Tirole (2010). Among the major barriers that hinder this process, one that is often cited —which is in line with Arrow's theory— is precisely the lack of market competition —Götz (1999), Vives (2008), and Correa and Ornaghi (2014). Therefore, if firms with market power are less prone to adopt new technologies, pro-environmental policies and regulation will become ineffective. Conversely, authors with a more Schumpeterian view would argue just the opposite. While many papers have presented numerous theoretical models to discuss the role of competition on technology adoption, ultimately this is an empirical question for which there is no clear-cut answer (perhaps due to the lack of natural experiments that allow researchers to claim causality) despite the huge policy implications —for instance, at the time of writing, the European Union discusses whether competition policies should be relaxed to achieve the environmental targets in the *European Green deal*.

Acknowledging the importance of this policy-relevant issue, in this paper we study whether an (exogenous) increase in competition induces suppliers to adopt new, green technologies. To answer this question, we use a unique dataset on all the vehicles purchased by professional taxi drivers in Spain between December 2014 and February 2020. We study the impact of the entry of well-known ride-hailing platforms —such as Uber and Cabify (a Spanish-based company)— across major metropolitan areas on their vehicle purchase decisions according to the type of engines, i.e., whether they are purely fossil-fuel-based or, alternatively, if they use cleaner engines (e.g. electric vehicles, hybrid vehicles, etc.). The staggered rollout of these platforms, which provides variation across metropolitan areas over time, allows us to study this question using a standard difference-in-differences approach.

As in many other countries, alternative-fueled (green) vehicles in Spain offer evident per-mile savings in comparison to those that run solely on petroleum products (diesel or gasoline), which are heavily taxed. However, the takeout of green vehicles is still very low among professional drivers.[1] Bearing in mind that the entry of the aforementioned ride-hailing platforms posed a thread on the dominance of the (long-lasting) incumbent taxi companies, we view their staggered rollout as a natural experiment to study whether a shock in the level of competition induced taxi drivers to purchase green vehicles more often. Importantly, contrary to previous works, our setup abstracts away from some other features, such as firms' strategic (marketing-related) "green investment" (i.e. those incurred to satisfy consumers' preferences for cleaner technologies), to focus solely on the impact that an increase in the intensity of market competition has on the incumbent suppliers' technology choices.

Our main findings are as follows. First, we find that the entry of these platforms significantly increased the takeout of green vehicles among taxi drivers. Our findings suggest that in metropolitan areas in which Uber and/or Cabify entered, the average monthly purchases of green vehicles increased by 27% relative to the "control" metropolitan areas. In other words, our estimates suggest that the entry of these platforms causally induced one extra green vehicle purchase by taxi drivers in every four. This finding is robust across different specifications and several robustness checks, and it also robust to the inclusion of lags that control for a potential anticipation effect. Moreover, additional data suggests that taxi drivers were not likely to delay the decisions to scrap their vehicles, and they were not likely either to purchase more used vehicles in the second-hand market following the entry of these platforms.

[1]According to the data from the Spanish Directorate-General for Traffic, 85% of the vehicles purchased in Spain by taxi drivers between December 2014 and February 2020 are powered solely by either diesel fuel (56%) or unleaded gasoline (29%).

In Spain, the number of vehicles that ride-hailing companies can operated is limited by local regulation —as a rule of thumb, one Uber or Cabify vehicle is allowed per every thirty taxi licenses.[2] Since Uber and Cabify typically deployed the maximum number of vehicles allowed at the regional level whenever they enter a metropolitan area, then it was extremely unlikely for them to enter also into another metropolitan area within the same region —due to the aforementioned regional (binding) limitation. As a consequence, taxi drivers in these latter metropolitan areas could anticipate that competition will be less intense for them. Consistently, we find that the effect on the takeout of different types of vehicles in these metropolitan areas is just the opposite to that found in cities where Uber and Cabify entered: taxi drivers did not significantly increase the purchase of green vehicles. In fact, our estimates suggest that they were more likely to buy dirty ones.

As mentioned above, our setup constitutes a close-to-ideal setting with which to study the effect of market competition on the adoption of new, green technologies by incumbent, dominant suppliers for several reasons. First, in all the metropolitan areas that we consider, the incumbent taxi companies enjoyed a dominant position with very limited (or no) competition —CNMC (2017). Thus, the entry of Uber or Cabify constitutes a shock in the intensity of competition that significantly reduced their market share. Moreover, this shock in the intensity of competition can be interpreted as an exogenous one, as the entry of these app-based, ride-hailing platforms usually responds to tourism or demographic-related reasons (e.g. population, number of international visitors), as documented by Berger et al. (2018).[3]

Second, the entry of ride-hailing platforms into local markets is unlikely to drive changes in the relevant characteristics of the incumbent taxi firms (prices, number of suppliers, productivity, etc.). Note that conventional taxi businesses are regulated by a limited number of medallions that grant drivers the right to serve consumers. The number of medallions very rarely changes in Spain at the metropolitan area level —certainly, it did not change after the entry of Uber or Cabify. Similarly, fares and drivers' working hours of conventional taxi companies (both heavily regulated) remain the same in the post-Uber (or post-Cabify) period in the cities that we consider.[4] This might not be the case in previous studies

[2]Uber and Cabify cannot operate as peer-to-peer ride-sharing platforms in this country. Instead, similarly to taxi companies, they provide ride-hailing services with professional drivers.

[3]In the same vein, we document that the entry of Uber and Cabify also respond to similar reasons in Spain. In particular, we find that they entered in cities with greater population, travelers, and unemployment (see Table A.1 in Appendix A).

[4]Anecdotal evidence suggest that one of the reactions of the incumbent taxi companies was to develop apps (similar to those used by Uber and Cabify) to hail a taxi. This favors the main argument of the paper, that is, that an increase in competition induces the adoption of new technologies (as no conventional taxi company used apps before the arrival of Uber/Cabify).

at the industry-level that rely on other type of shocks, such as trade liberalization (e.g. manufacturing sector) or deregulation (e.g. energy sector), in which additional competition —in combination with pro-environmental regulation— might induce incumbent firms to reallocate production or to exit the market, potentially overestimating the causal effect of competition on the diffusion of green technologies.

Third, taxi drivers' incentives to purchase green vehicles are unlikely driven by strategic or marketing-related purposes, that is, to attract customers with particular environmental preferences. This is because taxi drivers are typically anonymous: when a consumer hails a taxi, she cannot choose one car over another one based on the type of engine (customer choices are usually restricted to cab size) —Hall and Krueger (2018). Again, this might not be the case in some other sectors (e.g. electricity generation), in which customers might prefer one supplier over another due to environmental concerns and preferences, creating thus a strategic-investment effect on the suppliers.[5] Four, as Aghion et al. (2020) explain, the use of vehicles data is ideal and appropriate in this kind of studies, since the distinction between "clean" and "dirty" technologies is clear and highly relevant. This distinction is even easier in the Spanish context, as there is a government-approved sticker-based classification that easily identifies environmentally-friendly vehicles —additional details on these stickers are provided in Section 2.

This paper makes a contribution that is relevant for different strands of the literature. First and foremost, it is related to the recent and growing literature on market structure and green technologies. Perhaps the closest paper is by Aghion et al. (2020). These authors develop a model to document that firms innovate green to escape market competition, and validate their theoretical findings using data from the European automobile sector. However, part of their story is precisely that firms innovate green to attract consumers with certain environmental preferences. We abstract away from the role of consumers' preferences to focus solely on the "market competition" effect on technology choices. Another related paper is by Nesta et al. (2014), which documents that renewable energy subsidies are more effective in fostering green innovation in countries with liberalized energy markets. However, using liberalization as a proxy for the intensity of competition might also present some challenges, as we discussed above.

Our paper also adds to the literature that examines the effects of competition on innovation and technology diffusion in the presence of certain regulatory (industrial) policies. In that regard, Aghion et al. (2015) address the issue of complementary between market competition and industrial policies

[5] As explained by Woo and Zarnikau (2019), many electricity companies offer retail pricing plans with more renewable energy content (usually for a premium fee) to attract customer with certain environmental preferences.

along the lines of recent Schumpeterian models on innovation and competition —see e.g. Aghion et al. (2001) and Aghion et al. (2005). Using a theoretical framework, they find that policies targeted at sectors with higher technological potential have a larger effect on firms' innovative efforts, conditional on the absence of collusion. These theoretical findings are in line with our empirical results.

Regarding this strand of the literature, many papers have focused in particular on the energy sector, with an eye also on the role played by environmental regulation. For instance, Sanyal and Ghosh (2013) argues that the interplay between environmental policies and market liberalization is a key determinant of innovation. In the same vein, Jamasb and Pollitt (2011) observe that renewable patents have significantly increased in the post-liberalization period, and Asane-Otoo (2016) documents using aggregated data that higher competition has a positive impact on reducing emission in restructured electricity markets. However, identification in these papers might be threatened if, as Lee (2020) documents, market liberalization increases the likelihood of adopting policies that promote green investments (e.g. RPS and cap-and-trade). In addition, it might be potentially complicated to disentangle if the results are driven just by the increase in market competition, or also as natural reaction to the liberalization policies.

Finally, we also contribute to a recent literature on the economic impact of ride-hailing platforms (mostly focused on Uber). Most of these papers —with the notable exception of Berger et al. (2018), who studies the impact of the entry of Uber on wages earned by drivers in conventional taxi companies— focus on the consequences for Uber users and drivers. For instance, on the demand-side Cohen et al. (2016) documents substantial gains in consumer surplus associated to the launch of UberX. On the supply-side, Cramer and Krueger (2016) and Chen et al. (2019) show that drivers enjoy both the work flexibility and substantial increases in earnings that conventional taxi companies usually do not allow.

The rest of the paper proceeds as follows. In Section 2 we provide some background. The empirical strategy is discussed in Section 4. Section 5 presents the empirical results, and Section 6 concludes.

2 Background

In this section we provide some background on the taxi industry in Spain, and on the staggered rollout of ride-hailing platforms across different metropolitan areas.

2.1 The taxi business in Spain

In many countries, the conventional taxi business is a tightly regulated one with notorious entry barriers and restrictions —Cramer and Krueger (2016). In Spain, the regulation of the local taxi companies is implemented at the municipal level or at the metropolitan-area level either by the city hall or by some other local government agency.[6] The most commonly observed regulatory measures and restrictions are as follows.

First, the number of taxi drivers at the metropolitan area is limited by a system of medallions or licenses, which grant them the right to ride passengers. The number of medallions rarely changes. Therefore, drivers that are interested in joining the taxi business need to purchase these medallions in the secondary market.[7] Second, taxi drivers are restricted from picking up consumers outside of the jurisdiction that issued their license. Third, fares are heavily regulated, and common across all taxi drivers within the metropolitan area. These fares are usually established in a two-part tariff fashion —a minimum fee plus a linear (per-mile) fee—, with some price discrimination according to the time of use (e.g. night fares, bank holidays fares, etc.). Some other features, such as the color of the vehicles, are also regulated in some cities.[8] All these restrictions create huge entry barriers in the ride-hailing services market. As a consequence, local taxi companies have traditionally enjoyed a (*de facto*) monopolist position in this market in all major cities across Spain, as the Spanish National Commission on Markets and Competition (CNMC, in its Spanish acronyms) documents —see CNMC (2017).

The vast majority of the drivers that work for the local taxi companies in Spain are either self-employed or they work on behalf of some entrepreneur in exchange of a revenue-based royalty (commission). In both cases, either the taxi driver itself (or the entrepreneur) chooses and purchases the vehicle she uses in the business, considering not only the upfront payment, but also the per-mile cost of the vehicle as the key ingredients to calculate the expected return of the vehicle.[9] Both the number of hours and also (in many cities) the days in which taxi drivers are allowed to work are restricted and

[6]For instance, the city hall regulates the taxi company that operates in Madrid, but in Barcelona this is done by the *Àrea Metropolitana de Barcelona* (a supra-municipal body).

[7]As Angrist et al. (2017) explains, the limited supply of taxi medallions has made medallions into valuable assets, typically held by investors or fleet owners, and trading for hundreds of thousands of dollars.

[8]For instance, taxis must be painted white in Madrid, Valencia, and Sevilla (to name a few), and they must be black and yellow in Barcelona.

[9]In a few cities (e.g. Madrid), the set of vehicles that taxi drivers are allowed to purchase is restricted. However, the choice set is sufficiently ample, and includes vehicles of all sizes and types of engines.

regulated. Therefore, taxi drivers cannot increase the number of hours or days they pick up passengers to increase their return on the vehicles. In addition, they are not allowed to partner with Uber or Cabify (and they cannot secretly do, since taxis are painted with easily identifiable colors in most cities).

2.2 Entry of ride-hailing platforms across Spanish metropolitan areas

To compete with conventional taxi companies, two ride-hailing (app-based) platforms enter different metropolitan areas in Spain, namely Uber —a renowned multi-national company based in San Francisco— and Cabify —the locally founded alternative to Uber.[10]

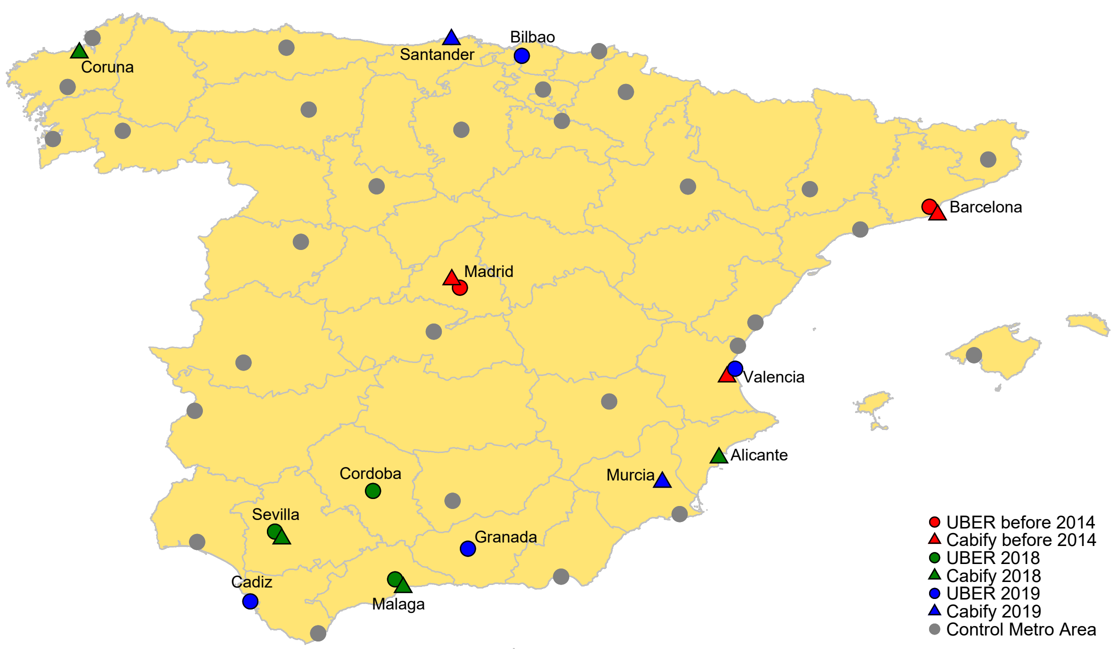
Uber launched its peer-to-peer ride-sharing services for the first time within Spain in Barcelona in April 2014. Then, this service was subsequently offered also in the metropolitan areas of Madrid (September 2014) and Valencia (October 2014). Even tough Uber became rapidly popular in these three cities within a few months —Spain was one of the fastest growing markets for this company at the time—, and following a fierce and violent opposition from conventional taxi drivers, a court banned Uber in December 2014, on the grounds that peer-to-peer ride-sharing services where not regulated as a legal activity in Spain. Following this prohibition, Uber was re-launched in Spain as a ride-hailing company with professional drivers. In March 2016, Uber offered back its services in Madrid, and it subsequently entered eight other major metropolitan areas across Spain, including Barcelona (March 2018), Malaga (June 2018), Sevilla and Cordoba (October 2018), Valencia and Granada (January 2019), Cadiz (July 2019), and Bilbao (November 2019).

Cabify was founded in Spain in 2011, and it started to operate in Madrid in February 2012. Unlike Uber, Cabify entered into the market not as a peer-to-peer, ride-sharing company, but as a ride-hailing company with professional drivers. Therefore, the Spanish court did not ban it in December 2014. Then, Cabify subsequently entered some other metropolitan areas, including Valencia (2014), Malaga (February 2018), Alicante (June 2018), Sevilla (September 2018), Coruña (December 2018), Barcelona (January 2019), Murcia (March 2019), and Santander (June 2019). Both Uber and Cabify entered different cities unexpectedly (as a surprise), and the time between the announcement of entry and the actual entry was usually short (about a month), limiting thus the possibility of substantial anticipation effects. A summary of the staggered rollout of these companies across Spain is provided in Figure 1.

[10]In many other countries there are app-based local firms that compete with Uber, such as Ola in India, Didi in China, and 99 in Brazil.

Following a fierce and intense opposition from drivers in conventional taxi companies, both Uber and Cabify were also regulated in Spain. More precisely, these two companies operate under the local regulations of ride-hailing, professional driver companies (in Spanish, *Vehículo de Transporte con Conductor* or VTC). Among other things, the number of vehicles that these companies can operate is capped at the regional level. The general rule is that the number of VTC vehicles cannot exceed one every thirty taxi licences —CNMC (2019). This upper limit is either binding or exceeded in all the provinces where Uber and Cabify entered. Despite the regulatory efforts to prevent the growth of these companies, there is substantial evidence that the entry of Uber and Cabify provided an unprecedented shock in the intensity of competition in the taxi industry in Spain, mostly due to the fact (unlike conventional taxi companies) Uber and Cabify use internet-based mobile technology to match passengers and drivers.[11] In the following we study to what extent this unexpected shock induced professional taxi drivers to switch from dirty vehicles to green ones.

Figure 1. Spatial diffusion of Uber and Cabify in Spain.



Note: The figure shows the map of the metropolitan areas in Spain that we consider in this study (all those with population greater than 100,000). Solid dots represent metropolitan areas in which Uber entered, and solid triangles represent those in which Cabify entered. Dots shaded in light gray represent the control metropolitan areas —those in which neither Uber nor Cabify entered. We also considered as control two metropolitan areas in the Canary Islands (Tenerife and Gran Canaria), which are not included in this map. Thin gray lines are boundaries of provinces.

[11] Akimova et al. (2020) document that Cabify and Uber had a significantly negative effect on the profitability of the traditional taxi companies. Similar evidence is also found in other countries. For instance, Ngo (2015) found that, in the USA and Canada, traditional taxi firms lost (at least) 10% to 40% of market share after the entry of app-based, ride-hailing platforms.

3 Empirical framework

3.1 Baseline regression model

To study the impact of the rollout of ride-hailing platforms across Spain on the composition of the fleet of conventional (incumbent) taxi companies, we examine the aggregated purchases of new vehicles by taxi drivers at the metropolitan area-month level. Our empirical strategy relies on variation both in the timing and place of entry of Uber and Cabify. Metropolitan areas without ride-hailing platforms during the period of our sample provide a natural control group, allowing us to identify the effect on the vehicle purchases before and after the entry of these platforms in the "treated" metropolitan areas (i.e. those in which Uber or Cabify entered). Our empirical model controls for some other underlying demand and supply-related variables and trends, as described below.

To accommodate the count data nature of the dependent variable (number of new vehicles purchased by taxi drivers by fuel type in the metropolitan area-month) in our panel data setting, we use a fixed-effects Poisson quasi-maximum-likelihood estimation with robust standard errors clustered at the province level to accommodate arbitrary patterns of correlation among the observations for each province —Wooldridge (1999), Fabrizio (2013), and McCabe and Snyder (2015).[12] Our main regression specification is as follows:

$$E\left(\text{Taxi}^{X}_{m,p,s,t} | Z_{m,p,s,t}, \lambda_m, \theta_t\right) = \exp\left(\alpha_1 \text{Uber/Cabify}_{m,p,s,t} + \alpha_2 Z_{m,p,s,t} + \lambda_m + \theta_t\right), \qquad (3.1)$$

where $\text{Taxi}^{X}_{m,p,s,t}$ is the aggregated number of type-X vehicles purchased by taxi drivers in metropolitan area m, province p, state s, and month t, where $X \in \{\text{Green}, \text{Dirty}\}$ —the distinction of green and dirty vehicles is provided below—;[13] $Z_{m,p,s,t}$ is a vector of regressors,[14] λ_m is a metropolitan area fixed effect, and θ_t are year-month indicator variables that control for common patterns of purchases of vehicles over time, including the impact of regional incentives and policies that apply to all metropolitan areas.

The previous regression model provides the standard difference-in-difference setup, which allow us to estimate the change in the number of green/dirty vehicles purchased by professional taxi drivers due

[12] As Wooldridge (1999) and Fabrizio (2013) explain, this method does not rely on the often-violated assumption of mean variance equivalence, while it provides consistent estimates under general conditions.

[13] A similar distinction between dirty and clean cars to study innovations in the automobile sector is in Aghion et al. (2016).

[14] Including also regressors at the province and state level.

to a shock in the level of competition in some metropolitan areas —where Uber or Cabify entered— relative to the metropolitan areas where these companies did not enter. We base our analysis on one major identifying assumption. Namely, we assume that the entry of Uber and/or Cabify in a metropolitan area are not correlated with unobserved factor that also affect the purchase of green/dirty vehicles by taxi drivers in the same metropolitan area after controlling for different underlying drivers of these purchases that vary across metropolitan areas and over time. This assumption is likely satisfy if we consider that, consistent with the information above, Uber and Cabify entry decisions are based on socio-demographic characteristics, such as population and number of visitors, while taxi drivers' vehicle purchase decisions are rather based on environmental policies, income, and/or fuel prices.

3.2 Model extensions: spillover effects

Our baseline model captures the entry of Uber or Cabify using a dummy at the metropolitan area level. However, there might be also some valuable information in those metropolitan areas in which these platforms did not enter, but that are within the same regional area (province) in which they did so.

As explained above, the number of vehicles that these ride-hailing platforms are allowed to operate is capped and, as suggested by official figures, in those regions in which they entered the maximum number of vehicles that the regulation allows them to operate —one in every in every thirty taxi licenses— is binding (or even exceeded). Therefore, taxi drivers in the cities in which Uber or Cabify did not enter but located within the same province in which they did so presumably might expect to remain in a dominant position in the market. Therefore, one should anticipate to find the opposite effect in the takeout of different types of vehicles by taxi drivers to that obtained for the cities in which Uber or Cabify actually entered.

To test this hypothesis, we augment our regression model as follows

$$E\left(\text{Taxi}^X_{m,p,s,t}|\cdot\right) = \exp\left(\beta_1 \text{Uber/Cabify}_{m,p,s,t} + \beta_2 \text{Uber/Cabify in Province}_{m,p,s,t} + \beta_3 Z_{m,p,s,t} + \lambda_m + \theta_t\right), \tag{3.2}$$

where Uber/Cabify in $\text{Province}_{m,p,s,t}$ is a dummy equal to 1 if Uber or Cabify did not entered metropolitan area m but entered some other metropolitan area m' located in province p, and equal to 0 otherwise.[15] In this alternative regression model β_2 is the parameter of interest, which captures the "lack-of-expected-

[15] None of these platforms entered more than one metropolitan area per province.

competition" effect on the number of new vehicles purchased by taxi drivers.

3.3 Validity and robustness checks

In this section we discuss some potential concerns of the regressions models above. The key identifying assumption for a difference-in-differences strategy is that, absent the intervention (the entry of Uber or Cabify), vehicle purchase patters among taxi drivers would have evolved similarly in metropolitan areas in which these companies entered and in those in which they did not do so. However, one might argue that in those cities in which Uber or Cabify entered, taxi drivers are perhaps more likely to use their current vehicles for longer time or, alternatively, to purchase second-hand vehicles more often.

We address this concern in two ways. First, we present alternative estimations using data on the number of vehicles scrapped by taxi drivers. In particular, we show using a similar Poisson regression approach that the number of vehicles scrapped by taxi drivers did not decrease to a greater extent in metropolitan areas in which Uber or Cabify entered *vis-à-vis* the control metropolitan areas. This result suggests that Uber and Cabify did not substantially decrease the depletion rate of the vehicles among taxi drivers. Second, we also estimate the impact of the entry of Uber and Cabify on the number of second-hand vehicles used as taxis that are sold at the metropolitan area-month level. Again, we do not find significant evidence that the rollout of these platforms induced additional purchases in the second-hand market among taxi drivers.

Next, we might be concerned of a potential anticipation effect in the purchase of green vehicles. Even though the entry of Uber or Cabify is usually announced by surprise, this entry does not happen overnight (on average, the time between the announcement of entry and the actual entry was one month). To address this concern, we augment our main regression model to include also a dummy that capture the period (month) right before the entry of these raid-hailing platforms in the corresponding metropolitan area. These additional dummy captures the potential existence of an anticipatory effect.

A third potential concern is that the metropolitan areas in which Uber or Cabify entered (treated) are substantially different than those in which these companies did not entered (control). In fact, in Appendix A we provide some evidence that the former ones tend to have *(i)* greater unemployment, *(ii)* more tourists, and *(iii)* higher population. As a result, one might argue that the treated and control metropolitan areas are not well matched. We address this potential concern using a propensity score matching technique. We estimate the propensity of metropolitan areas to have Uber or Cabify as a function of these three (exogenous) characteristics. Then, we trim our sample to drop the metropolitan areas that do not have common support and we re-estimate equation 3.1 using this subsample.

4 Data and Summary Statistics

To estimate the impact of the rollout of ride-hailing platforms on the fleet of taxis at the local level, we combine publicly available secondary data from disparate sources together with the set of dummies that capture the entry of Uber and Cabify in different metropolitan areas in Spain —see Figure 1— and some other indicators. By combining all this information, we create a novel panel data at the metropolitan area-month level, covering the period December 2014–February 2020.

Data on vehicles purchased. To begin with, data on all the new vehicles purchased by professional taxi drivers in Spain was downloaded from the Spanish Directorate-General for Traffic (DGT, in its Spanish acronyms).[16] This dataset includes information on the type of vehicle purchased (engine, size, brand, etc.) and also provides some characteristics of the buyer (city of residence, date of the purchase, etc.). We focus on all purchases of regular (5-passenger) vehicles by taxi drivers in the metropolitan areas included in the map in Figure 1 between December 1, 2014 and February 28, 2020, which we aggregate by month.

To differentiate between types of vehicles (i.e., green or dirty), we take advantage of the system of stickers implemented (nationwide) by the Spanish government, which identifies green vehicles (i.e., those that are not powered exclusively by diesel fuel or unleaded gasoline) with either an "Eco" sticker or a "Zero" sticker —as provided in Figure 2.[17] The Eco sticker is granted to all plug-in hybrid electric vehicles (PHEV) that can travel up to 40 kilometers (around 25 miles) without using its combustion engine, hybrid electric vehicle (HEV) —those that combine a conventional internal combustion engine system with an electric propulsion system—, and all natural gas powered vehicle, including those that use compressed natural gas (CNG) or liquefied natural gas (LNG).[18] The Zero sticker is granted to all

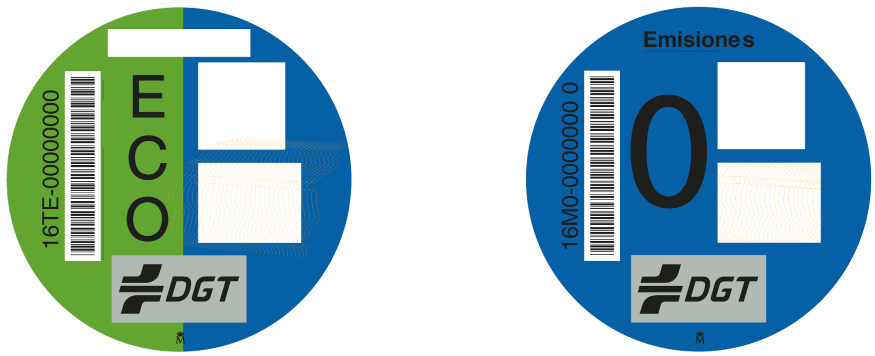
[16]This dataset includes only the vehicles purchased by professional drivers in conventional taxi companies. It does not capture those purchased by professional drivers working for some other companies (including Uber and Cabify), as these purchases are separately identified as made by professional VTC drivers.

[17]A similar system of stickers is used in many other countries within the European Union —Haq and Weiss (2016) and Alberini et al. (2019).

[18]Recent research provides evidence that emissions from CNG and LNG are substantially lower compared to those by

battery electric vehicle (BEV), range-extended electric vehicles (REEV), hydrogen internal combustion engine vehicles (HICEV), plug-in hybrid electric vehicles (PHEV) that can travel more than 40 kilometers (25 miles) without using its combustion engine, and fuel cell vehicles (FCV). In our empirical analysis, dirty vehicles are those not allowed to carry one of these stickers.[19]

Figure 2. Stickers granted to green vehicles in Spain.



(A) Eco sticker

(B) Zero sticker

Note: The figure provides the stickers used in Spain to identify green vehicles. The Eco sticker —Subfigure 2(A)— identifies all plug-in hybrid electric vehicles (PHEV) that can travel up to 40 kilometers without using its combustion engine, hybrid electric vehicle (HEV), and all natural gas powered vehicle —compressed natural gas (CNG) or liquefied natural gas (LNG) vehicles. The Zero sticker —Subfigure 2(B)— identifies all battery electric vehicle (BEV), range-extended electric vehicles (REEV), hydrogen internal combustion engine vehicles (HICEV), plug-in hybrid electric vehicles (PHEV) that can travel more than 40 kilometers without using its combustion engine, and fuel cell vehicles (FCV).

Even tough green vehicles are usually more expensive *vis-à-vis* their conventional gasoline and diesel counterparts, it is well-documented that they provide substantial per-mile savings, particularly to relatively high-kilometer drivers (such as taxi drivers) —Hoekstra et al. (2017) and Li et al. (2017). These per-mile savings (and some other benefits) are usually the result of different policies that promote their purchase. For instance, driving dirty vehicles in Spain is penalized through a tough taxation of petroleum refined products —subsidies to purchase green vehicles are residual in this country. In addition, some Spanish cities implemented low-emission zones (LEZ), in which only green vehicles are allowed to enter.[20] Despite all these regulatory efforts, aggregate figures suggest that the takeout of green vehicles is

gasoline and diesel fueled vehicles —Takeuchi et al. (2007), Rood Werpy et al. (2010), Murphy (2010), and Knittel (2012).

[19]Biofuel-powered vehicles are not considered as green vehicles in Spain. In any case, there is only one biofuel-powered vehicle purchased by a taxi driver in our sample, which we drop.

[20]Madrid and Barcelona implemented very ample and stringent LEZs, in which vehicles without these stickers are not allowed to enter. For these particular cities, one might be concerned that the takeout of green vehicles among taxi drivers was driven not by the intensity of competition, but due to the implementation of LEZs, as suggested by Wolff (2014). Therefore, we remove data from Madrid and Barcelona in our analysis.

still relatively low, both among professional and non-professional drivers. For instance, according to the DGT, 56% of the vehicles purchased in Spain by taxi drivers between December 2014 and February 2020 are powered solely by diesel fuel (which remains as the most popular fuel used by professional drivers), while 29% are powered only by unleaded gasoline.

Additional variables. To confer robustness to our model, we add variables that allow us to control for the conditions of the taxi business at the local level, the general socioeconomic scenario, the environmental awareness, and the automobile industry. To being with, to control for socio-economic conditions and the purchasing power that might affect taxi drivers in different regions in Spain, we obtained data on both the unemployment rate and the mean income per-capita at the province level, obtained from (government-sponsored) official sources[21]. In addition, to control for political-preferences, we also include a set of dummies that capture both the political party in power in the city and in the State in which the city is located.[22]

Next, we also add some variables that are likely to affect taxi drivers' vehicle purchase decisions. First, we included data on the regional (State-level) fuel tax rate to capture differences in the fiscal policies aimed at reducing the purchase of fossil fuels for transportation purposes. This information was obtained from the different regional (State) tax legislation. Moreover, to capture idiosyncratic preferences for different types of cars, we also add as a control the total number of new "Eco" and "Zero" vehicles purchased in Spain by households and private users (i.e. excluding taxi drivers and other professional drivers), to rule out the possibility that the change in the purchase of green taxis is driven by a trend in the automotive sector. This information was also obtained from the DGT. Finally, due to the strong interdependence between tourism and the taxi business (and also considering that tourism is one of the most important sectors in the composition of the GDP in Spain), we add data on the monthly number of travelers at the province, which we downloaded from the Spanish National Statistics Institute (INE, in its Spanish acronyms). This information includes the number of visitors that spend one night or more in any of the registered hotel establishments in the province.

Sample. We use data from all the metropolitan areas across Spain with population greater than

[21] Income data at the province level, which is obtained from survey data, is not available for all the months included in our sample.

[22] There are no elections to choose representatives at the province level in Spain. Provincial leaders are chosen by the (elected) city-level representatives of all the municipalities within the province.

100,000, which are indicated in the map in Figure 1, plus the two main metropolitan areas in the Canary Islands (both have more than 100,000 inhabitants as well), which are not included in the map. In our sample, metropolitan areas encompass not only the main cities included in each of them, but also all the surrounding suburbs and cities in which the local (monopolist) taxi companies are allowed to pick up passengers. For instance, for the particular case of Barcelona, the metropolitan area is defined not only by the boundaries of the city of Barcelona itself, but it also includes all the 36 cities in the so-called *Àrea Metropolitana de Barcelona*, in which the local taxi company is allowed to operate. The same criterion was used for all the other cities in our sample.[23]

Table 1. Summary Statistics: Panel Data including 42 metropolitan areas over 63 months ($N = 2,583$)

	Mean	Std. deviation	Min	Max	N
Green vehicles (taxi)	1.816	2.893	0	24	2,583
Dirty vehicles (taxi)	3.768	4.650	0	44	2,583
Uber/Cabify	0.055	0.229	0	1	2,583
Uber/Cabify in province	0.025	0.155	0	1	2,583
(log)-Unemployment	11.363	0.653	9.899	12.766	2,583
(log)-Income	7.035	0.289	5.011	7.937	2,098
(log)-Travelers	11.61	0.852	9.668	14.414	2,542
Fuel duties (diesel)	4.458	0.231	4.005	4.586	2,457
% Eco cars (priv. use)	5.021	3.603	0	21.6	2,583
% Zero cars (priv. use)	0.498	0.688	0	6.818	2,583
Observations	2,583				

Note: Summary statistics for all the variables included in our final dataset, except for the political parties dummies (both at the State and at the city level). "Green vehicles (taxi)" capture the vehicles purchased by taxi drivers that are suitable to carry either Zero sticker or an Eco sticker, while "Dirty vehicles (taxi)" are those vehicles purchased by taxi drivers that are not allowed to carry one of these stickers. All the variables are captured at the metropolitan area-month level, expect for unemployment, income, travelers —which are captured at the province-month level—, and fuel taxes —which is captured at the State-month level.

In our main empirical analysis, we drop data from two metropolitan areas, namely, Madrid and Barcelona. We do so for two important reasons. First, as indicated in Figure 1, Uber entered these cities well before the first month for which we have data on the purchase of vehicles (December 2014). The lack of pre-treatment (i.e. pre-Uber or Cabify) data on these cities does not allow us to capture the effect on the entry of platforms on the takeout of vehicles in them. Second, unlike the rest of the cities in our sample, both Madrid and Barcelona implemented aggressive Low-Emission Zones (LZE) in vast areas in the city center which, as documented by Wolff (2014), are likely to discourage the purchase of dirty

[23]The dummies that capture the political party in power at the city are based on those in power in the main city within each metropolitan area.

vehicles. Therefore, for these two cities, we do not know whether the impact on the purchase of green vehicles is driven by the increase in the intensity of competition caused by the entry of Uber and Cabify, or by the implementation of the LEZ itself.[24] Our final sample covers data from 41 major metropolitan areas at the month level. Table 1 contains summary statistics for them for all the aforementioned variables.

5 Empirical results

5.1 Main results

We present the empirical results from equation 3.1 in Table 2. We show the estimates of the effect of the entry of Uber or Cabify on the purchase of new vehicles by taxi drivers, distinguishing between green vehicles (those with either Eco or Zero sticker) in Columns (1)-(4); and dirty vehicles (those not allowed to carry one of these stickers) in columns (5)-(8).

First, we focus on the results using green vehicles data. Column (1) presents the estimates of the effect of the rollout these platforms on the takeout of green taxis, controlling only for unemployment at the province level and the dummies of the political parties in the city and the State (as well as the aforementioned metropolitan-area and month fixed effects). The estimated coefficient is positive and significant at the 1% level, suggesting that the entry of Uber or Cabify increased the takeout of green vehicles among taxi drivers by 28%. The estimated marginal effect obtained from this coefficient suggests that these platforms causally induced on average one extra green vehicle purchase in every four in the metropolitan areas in which they entered relative to the control ones.

Next, in Column (2) we include the full set of control variables described above —except income at the province level, due to the substantial number of missing observations— and also a dummy that captures the month before the entry of Uber or Cabify in the corresponding metropolitan area, to capture a potential anticipatory effect by taxi drivers.[25] Column (3) includes the full set of controls (except income), the lagged dummy for Uber/Cabify entry, and also state-specific time trends that account

[24] Cabify also entered Valencia before 2014, but there is no LEZ in that city. We drop this city for our main analysis, but the empirical results are the same with and without Valencia.

[25] Uber and Cabify usually entered different cities in Spain unexpectedly (as a surprise). However, according to the World Bank, the time required to start a business in Spain is about 13 days. Therefore, we should not expect a substantial anticipation effect more than a month before the entry of these companies.

Table 2. Impact of Uber/Cabify entry on takeout of different types of vehicles by taxi drivers

	Green vehicles				*Dirty vehicles*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Uber/Cabify	0.277***	0.271***	0.286***	0.283***	-0.0697	-0.0467	0.0110	0.0252
	(0.0973)	(0.0875)	(0.0804)	(0.0842)	(0.0794)	(0.0739)	(0.0706)	(0.0795)
(log)-Unemployment	0.403*	0.770*	0.425	0.227	0.0781	0.0600	-0.0434	0.0166
	(0.244)	(0.420)	(0.307)	(0.307)	(0.0930)	(0.269)	(0.175)	(0.179)
Fuel duties (diesel)		-0.576*	-0.381	-0.531		-0.453	-0.00986	-0.128
		(0.347)	(0.290)	(0.343)		(0.357)	(0.194)	(0.198)
(log)-Travelers		0.152	0.0905	-0.00689		0.00899	-0.0145	-0.00939
		(0.117)	(0.0976)	(0.104)		(0.0778)	(0.0573)	(0.0637)
% Eco cars (priv. use)		0.00453	-0.00105	-0.00803		0.00848	0.0105	0.000802
		(0.0132)	(0.0158)	(0.0185)		(0.0145)	(0.0144)	(0.0151)
% Zero cars (priv. use)		0.0313	0.0143	-0.0254		0.00632	-0.0299	-0.00219
		(0.0397)	(0.0371)	(0.0381)		(0.0339)	(0.0344)	(0.0359)
Uber/Cabify (t-1)		-0.0895	-0.121	-0.0444		-0.0549	-0.0756	-0.147
		(0.161)	(0.156)	(0.182)		(0.0998)	(0.0936)	(0.104)
(log)-Income				0.0401				0.0664
				(0.0798)				(0.0781)
Polit. party City dummies	✓	✓	✓	✓	✓	✓	✓	✓
Polit. party State dummies	✓	✓	✓	✓	✓	✓	✓	✓
Metro Area fixed effect	✓	✓	✓	✓	✓	✓	✓	✓
Month fixed effect	✓	✓	✓	✓	✓	✓	✓	✓
State-specific time trend			✓	✓			✓	✓
Pseudo R^2	0.450	0.453	0.460	0.465	0.489	0.484	0.490	0.501
N. Observations	2,567	2,383	2,383	1,959	2,583	2,389	2,389	1,965

Standard errors clustered at the province level in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

for additional but unobserved factors that vary within states over time, such as policies to promote the purchase of green vehicles (which are mostly implemented at the State level). Finally, column (4) includes all the above plus income at the province level as an additional control variable. In these three columns, the estimated effect remains positive, significant at the 1% level, and very similar in magnitude to that obtained in Column (1).

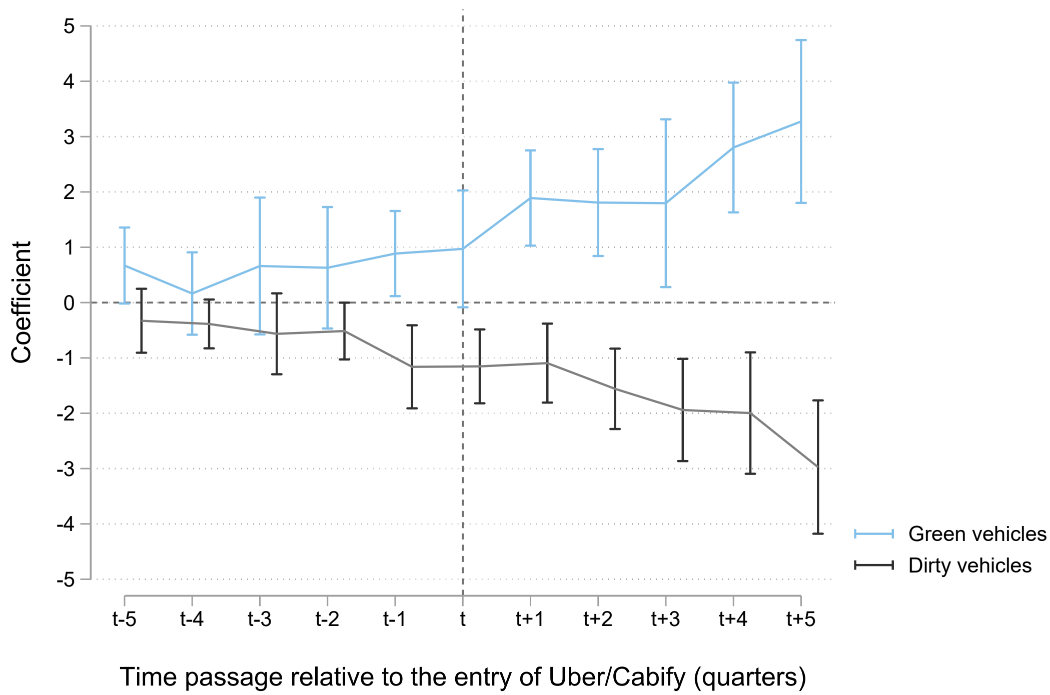
We next turn to discuss the effect of the entry of the aforementioned ride-hailing platforms on the purchase of dirty vehicles by taxi drivers. Column (5) includes the results controlling only for unemployment, political parties at the city and state level. In column (6) we provide the estimates using also all the other control variables (expect income) and the dummies that captures the lag of Uber or Cabify entry. Column (7) includes also the State-specific time trend, while column (8) adds income at the province level as an additional control variable. In all these cases the coefficient of interest (α_1) is close to zero and not significant. Overall, our results suggest that the shock in the intensity of competition caused by the entry of Uber and Cabify increased the purchase of green vehicles among taxi drivers —as shown in columns (1)-(4)—, while purchases of dirty vehicles remained unchanged —as shown in columns (5)-(8).

To further see the differences between green and dirty vehicles purchased by taxi drivers, we plot the estimated coefficients of the impact of the entry of Uber on takeout of different types of vehicles over time. To do so, we extend our main regression model —equation 3.1— by including several leads and lags of the entry of Uber/Cabify variable, which allow us to check not only the impact before and after the entry of these platforms on the takeout of different vehicles, but also to check potential pre-trends.[26]

The results of this exercise are included in Figure 3. The light colored line represents the impact of the entry of these platforms on the takeout of green vehicles by taxi drivers five quarters before and after the quarter in which these platforms were launched in the corresponding local market, while the black line captures the same but for dirty cars (both lines include 95% confidence intervals). Both lines show that the effect from 5 quarters to 2 quarters before the entry of the ride-hailing platforms is not significant, ruling thus out the possibility of pre-trends. The results also suggest that there might be a slight anticipation effect, as there is some evidence (slightly significant) suggesting that the takeout of green vehicles increased and that or dirty vehicles decreased right before then entry of Uber/Cabify.

[26] As explained above, pre-trends due to an anticipation effect are unlikely to occur, considering that the time between the announcement and the actual entry of Uber and Cabify in a city is usually short.

Figure 3. Takeout of different types of vehicles by taxi drivers relative to the time of entry of Uber and Cabify.



Note: This figure captures the impact that Uber/Cabify had on the takeout of green and dirty vehicles by taxi drivers five quarters before and after the quarter in which these platforms entered the corresponding the local markets. The vertical dashed line represents the quarter in which Uber/Cabify entered the market. We augmented the model in equation 3.1 by adding leads and lags. The coefficients were obtained by estimating the model with the full set of control variables (except income), with standard errors clustered at the province level. The same set of results including also State-specific time trends are included in the Appendix.

However, the gap between both lines substantially widens from the quarter in which these platforms enter on. These results further suggest that the entry of these platforms trigger the purchase of green vehicles among taxi drivers relative to dirty ones.

5.2 Additional results: spillover effects

Next, we present the empirical results from equation 3.2, in which we also include the dummy that equals one if Uber or Cabify did not enter metropolitan area m in province t, but if they did so in some other metropolitan area m' within the same province t. As we extensively argued above, taxi drivers in these metropolitan areas presumably do not expect to face a increase in the intensity of competition, which lead us to anticipate that the estimated impact on the purchase of vehicles in these metropolitan areas (captured by β_2) is substantially different relative to that found in the previous subsection.

Table 3. Impact of Uber/Cabify entry in cities within the same province on takeout of different types of vehicles by taxi drivers

	Green vehicles				*Dirty vehicles*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Uber/Cabify	0.265**	0.234**	0.216**	0.264***	-0.0565	-0.0385	-0.0235	0.0587
	(0.105)	(0.0923)	(0.0996)	(0.0945)	(0.0897)	(0.0795)	(0.0844)	(0.0877)
Uber/Cabify in province	-0.310	-0.324	-0.287	-0.162	0.192+	0.242**	0.278*	0.301*
	(0.341)	(0.281)	(0.338)	(0.355)	(0.122)	(0.123)	(0.147)	(0.174)
Full set of controls		✓	✓	✓		✓	✓	✓
Uber/Cabify entry lag			✓	✓			✓	✓
Polit. party City dummies	✓	✓	✓	✓	✓	✓	✓	✓
Polit. party State dummies	✓	✓	✓	✓	✓	✓	✓	✓
Metro Area fixed effect	✓	✓	✓	✓	✓	✓	✓	✓
Month fixed effect	✓	✓	✓	✓	✓	✓	✓	✓
State-specific time trend				✓				✓
Pseudo R^2	0.450	0.458	0.460	0.466	0.490	0.495	0.496	0.502
N. Observations	2,567	1,988	1,949	1,949	2,583	1,994	1,955	1,955

Standard errors clustered at the province level in parentheses
$^{+}$ $p < 0.15$, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

We include our empirical results in Table 3. Again, estimates using green vehicles data are reported in columns (1)-(4), while those obtained using dirty vehicles data are included in columns (5)-(8). Consistent with the explanations above, we find that the coefficient if interest (β_2) is negative and not significant any more. That is, regardless of model specification that we use, we do not find evidence that the taxi drivers in metropolitan areas in provinces in which Uber or Cabify did not enter, but located within the same province in which they did so increased the purchase of green vehicles.

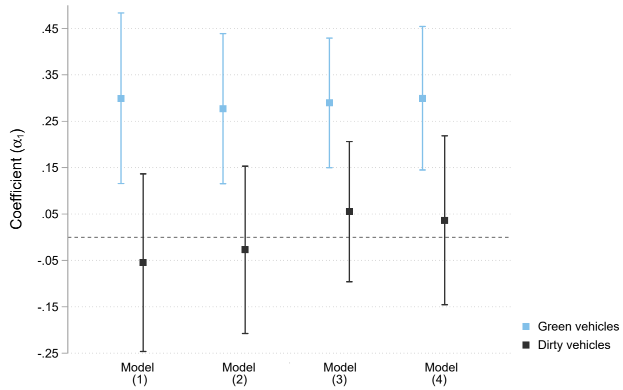
However, just the opposite effect is observed for the case of dirty vehicles. That is, while taxi drivers in cities in which Uber or Cabify entered did not increased the purchase of dirty vehicles, the taxi divers in cities within the same province just started to do so —β_2 is positive in columns (5)-(8). This coefficient is only marginally significant in the model that does not include control variables, but it becomes significant either at the 5% or 10% level as we successively add the full set of control variables —column (6)—, the lagged dummy for Uber/Cabify entry —column (7)—, and the State-specific time trend —column (8). In the latter case, the coefficient indicates that taxi drivers that were unlikely to expect a positive shock in the intensity of competition increased the average monthly purchases of dirty vehicles by about 30%.

5.3 Robustness checks

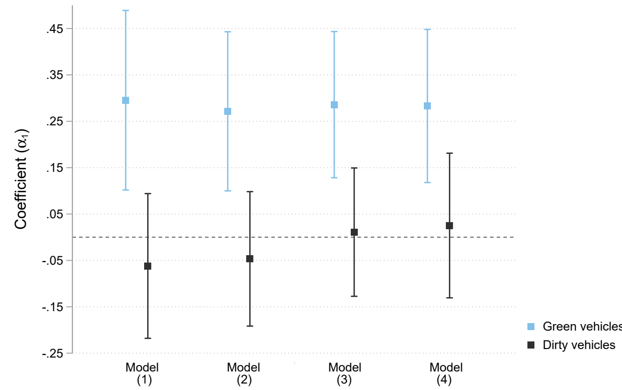
In this section we present some additional results that support our main findings. First, as explained above, one might be concerned that the metropolitan areas in which Uber or Cabify entered are not well matched with those in which these companies did not entered. In fact, we provide some evidence that these companies entered in metropolitan areas that have, on average, higher population, more tourists, and higher unemployment rates. We address this potential concern using a propensity score matching technique. We estimate the propensity of metropolitan areas to have Uber or Cabify, as a function of these three characteristics, and we drop those that do not have common support. We then re-estimate equation 3.1 using these trimmed subsamples.

The main results of this exercise are included in Figure 4. We present the coefficient of interest in equation 3.1 (α_1) using both the data on green vehicles (light blue squares) and on dirty vehicles (black squares) by matching our metropolitan areas by population —subfigure 4(A)—, number of tourists —subfigure 4(B)—, unemployment —subfigure 4(C)—, and finally using all the aforementioned variables —subfigure 4(D). The estimates are very similar to those obtained with the full sample. In particular, the coefficient of interest (α_1) is positive, significant, and equal to 0.27 in all the specifications of the

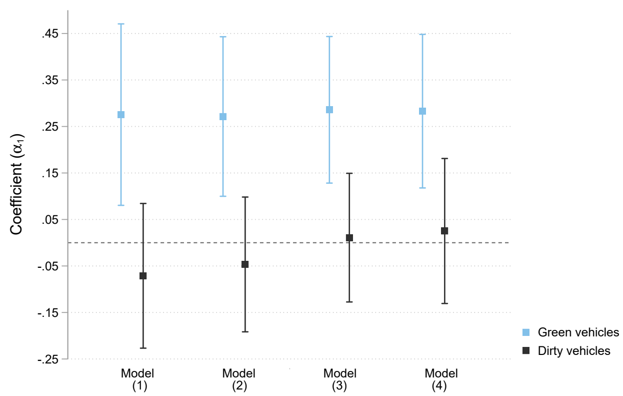
Figure 4. Estimated impact of Uber/Cabify entry on takeout of different types of vehicles by taxi drivers using different subsamples of matched metropolitan areas



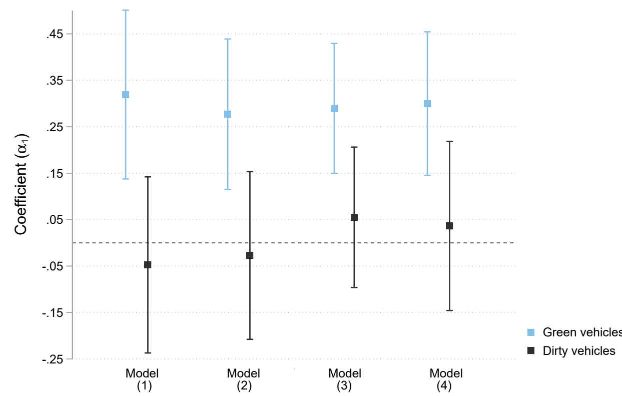
(A) Metropolitan areas matched by population



(B) Metropolitan areas matched by number of tourists



(C) Metropolitan areas matched by unemployment



(D) Metropolitan areas matched by all the above

Note: The figure displays the estimated coefficient of interest in equation 3.1 (α_1) by using different subsamples of metropolitan areas, obtained from a propensity score matching technique. Subfigure 4(A) presents the results after matching the metropolitan areas by population. In Subfigure 4(B) we match them by the number of tourists. In Subfigure 4(C) we match them by unemployment. Finally, in Subfigure 4(D) we match them using all the previous variables. In all cases, we dropped the metropolitan areas that are not under common support. The coefficients were obtained by estimating equation 3.1 using no controls —Model (1)—, the full set of controls (except income) —Model (2)—, the full set of controls (except income) plus State-specific time trends —Model (3)—, and the full set of controls (including income) plus State-specific time trends —Model (4). Standard errors are clustered at the province level.

regression models using the green vehicles data. That is, we obtain the same result if no control variables are included —Model (1)—, if we include the full set of control variables (except income) —Model (2)—, if we also add the State-specific time trends —Model (3)—, and if we also include income as an additonal control —Model (4). However, for all these specifications, α_1 is close to zero and not significant when we use data on dirty vehicles.

Another potential concern is that the pattern in the purchase of vehicles by taxi drivers might substantially change after the entry of Uber or Cabify. In particular, one might think that, given the shock in competition, taxi drivers in these metropolitan areas were more likely to purchase used vehicles, and/or to use their current vehicles for longer periods of time. If this were the case, this would affect (underestimate) our results.

Table 4. Impact of Uber/Cabify entry in cities within the same province on the takeout of different types of used (second-hand) vehicles by taxi drivers

	Green vehicles			*Dirty vehicles*		
	(1)	(2)	(3)	(4)	(5)	(6)
Uber/Cabify	0.0591	-0.0724	-0.318	0.0383	0.0252	0.0558
	(0.179)	(0.201)	(0.244)	(0.0780)	(0.105)	(0.109)
Full set of controls		✓	✓		✓	✓
Uber/Cabify lag		✓	✓		✓	✓
Polit. party dummies	✓	✓	✓	✓	✓	✓
Metro Area fixed effect	✓	✓	✓	✓	✓	✓
Month fixed effect	✓	✓	✓	✓	✓	✓
Pseudo R^2	0.318	0.314	0.325	0.297	0.277	0.281
N. Observations	2,518	1,908	1,908	2,583	1,965	1,965

Standard errors clustered at the province level in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

To rule out this possibility, we re-estimate equation 3.1 but we use instead as the outcome variable either the number of second-hand vehicles purchased or the the number of vehicles scrapped by taxi drivers per month.[27] The results of these two regressions are included in Tables 4 and 5 respectively. In both cases, all the coefficients are not significant for both types of vehicles. Overall, these results suggests that taxi drivers were unlikely to purchase more second-hand cars or to use their current vehicles for

[27]We obtained this data also from the DGT.

Table 5. Impact of Uber/Cabify entry in cities within the same province on the number of vehicles scrapped by taxi drivers

	Green vehicles			*Dirty vehicles*		
	(1)	(2)	(3)	(4)	(5)	(6)
Uber/Cabify	0.231	0.123	-0.125	0.0604	0.0448	0.107
	(0.213)	(0.265)	(0.238)	(0.0834)	(0.0924)	(0.114)
Full set of controls		✓	✓		✓	✓
Uber/Cabify lag		✓	✓		✓	✓
Polit. party dummies	✓	✓	✓	✓	✓	✓
Metro Area fixed effect	✓	✓	✓	✓	✓	✓
Month fixed effect	✓	✓	✓	✓	✓	✓
Pseudo R^2	0.272	0.276	0.289	0.378	0.364	0.370
N. Observations	2,280	1,698	1,698	2,583	1,965	1,965

Standard errors clustered at the province level in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

longer periods of time following the entry of these ride-hailing platforms.

6 Conclusions

Does market competition promote sustainability? From an intellectual point of view, this question has sparked an intense debate among economist that finds its roots in the long-lasting discussions on whether competition promotes the diffusion of new technologies —as the Arrowian view supports— or, to the contrary, whether market power is necessary to promote technological innovation —as the Schumpeterian view advocates. However, the question on the role of competition on the adoption of new, clean technologies has also become an extremely important one from a policy perspective in recent years. For instance, within the European Union, countries are currently profoundly discussing whether competition policy and antitrust should be modified (relaxed) to achieve the policy initiatives and environmental targets included in the so-called European Green deal. However, providing a clear answer to the question of interplay between the intensity of competition and the diffusion of green technologies has been usually challenging, due to the lack of settings that allow researchers to claim causality from one to the other.

In this paper, we aim at providing a straightforward answer to this question using a particular empirical setting that provides some of the key ingredients that allow us to isolate the effect of an (exogenous) shock in the intensity of competition on the adoption of clean technologies by dominant, incumbent suppliers. In particular, we study the takeout of green vehicles by professional taxi drivers before and after the entry of ride-hailing, app-based platforms —namely, Uber and its locally-founded rival Cabify. This setting constitutes an ideal setting with which to explore this question, considering that *(i)* the rollout of these platforms is unrelated to the vehicle choices by professional drivers in conventional taxi companies, *(ii)* their entry is unlikely to trigger relevant changes in the key characteristics of the incumbent taxi companies (prices, number of licenses, productivity, etc.), and *(iii)* taxi drivers' incentives to purchase green vehicles are unlikely driven to attract customers with particular environmental preferences.

Using a unique panel data on all the vehicles purchased by taxi drivers between December 2014 and February 2020 (in combination with some other supply and demand-related variables) we document that the staggered rollout of Uber and Cabify across major metropolitan areas in Spain substantially increased their takeout of green vehicles. More precisely, our results suggest that these platforms causally induced one extra green vehicle by taxi drivers in every four purchases, while no change is observed in their purchase pattern of dirty vehicles. Moreover, our results show that the exact opposite effect is observed in the behavior of taxi drivers in metropolitan areas in which Uber and Cabify are unlikely to enter.

Although market regulation and fiscal policies are usually acknowledged as necessary tools that allow firms to internalize the additional costs generated and, consequently, to effectively tackle negative environmental externalities and to induce firms to adopt cleaner production processes, our results suggest that they might not be sufficient ones —particularly if firms enjoy substantial market power. In those cases, a stringent and rigorous set of competition policies could actually be the way to effectively guarantee sustainability. Competition forces firms to adopt more efficient technologies (as induces firms to minimize costs) and to innovate, resulting in welfare benefits not only for consumers but for societies as a whole.

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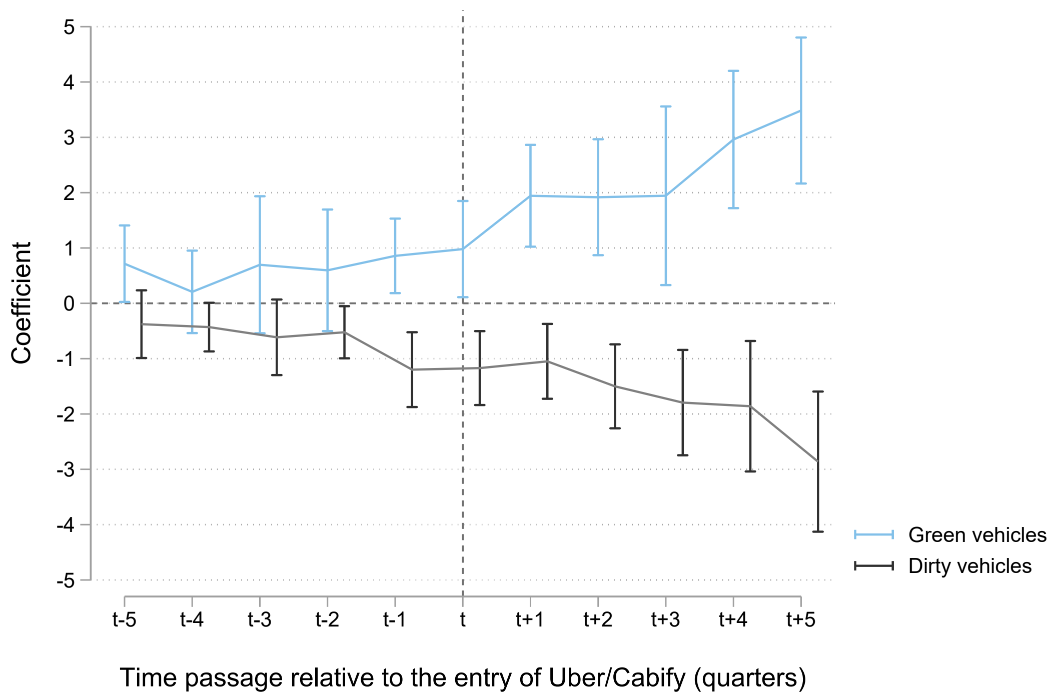
Appendix A (For Online Publication). Additional Figures and Tables

Table A.1. Balance of variables across metropolitan Areas with and witout Uber/Cabify

Variable	(1) Metro Areas without Uber/Cabify	(2) Metro Areas with Uber/Cabify	(3) Diff.
(log)-Population	12.398	13.329	0.931***
	(0.580)	(0.443)	(0.000)
(log)-Travelers	11.463	12.067	0.604***
	(0.862)	(0.632)	(0.000)
(log)-Unemployment	11.183	11.920	0.737***
	(0.600)	(0.469)	(0.000)
(log)-Bus users	8.503	8.366	-0.138***
	(0.443)	(0.365)	(0.007)
% Eco cars (priv. use)	5.031	4.992	-0.040
	(3.751)	(3.106)	(0.792)
Observations	1,953	630	2,583

Figure A.1. Takeout of different types of vehicles by taxi drivers relative to the time of entry of Uber and Cabify (estimates with State-specific time trends).



Note: This figure captures the impact that Uber/Cabify had on the takeout of green and dirty vehicles by taxi drivers five quarters before and after the quarter in which these platforms entered the corresponding the local markets. The vertical dashed line represents the quarter in which Uber/Cabify entered the market. We augmented the model in equation 3.1 by adding leads and lags. The coefficients were obtained by estimating the model with the full set of control variables (except income) and State-specific time trends, with standard errors clustered at the province level.