Peer Effects in Electric Car Adoption: Evidence from Sweden

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Abstract

I study peer effects in the diffusion of electric cars in Sweden among co-workers, relatives, and neighbors. To identify peer effects, I exploit a shift-share IV design linking expiring leasing contract renewals (i.e., shift) with the propensity to acquire an electric car based on individual traits (i.e., share). One new electric car causes, in the next quarter, .094 new electric car acquisitions in the workplace, .023 in the family, and .22 in the neighborhood. These peer effects displace fossil fuel cars and are associated with the transmission of information. I develop a framework highlighting how incorporating peer effects shifts optimal environmental policies.

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I. Introduction

How to promote a shift toward new environmentally-friendly technology is a central issue in economic and policy debates over the green energy transition. The transport industry accounts for about a quarter of Europe's greenhouse gas emissions and is the only sector where emissions have not decreased since 1990 (European Environment Agency, 2023). Reducing transport emissions is pivotal to meeting the EU's emissions targets and ensuring progress toward its 2050 objective of climate neutrality. To transition to low-emission mobility, Europe plans to replace vehicles powered by the combustion of fossil fuels with electric vehicles (EV). However, the market penetration of EVs remains relatively low and insufficient to reach the set EU emission targets.

A key mechanism in the diffusion of new technologies and practices is social interactions with peers (Griliches, 1957; Bass, 1969).[1] Early adopters of new technologies can generate positive externalities among their peers, which impacts the technology's diffusion process. Therefore, environmental policies that aim to stimulate the diffusion of new, environmentally-friendly technologies must incorporate how peer effects influence the adoption decision in social networks.

My primary contribution is to provide causal estimates of peer effects on adopting a crucial new green technology – electric cars[2] – within peer groups that span essential aspects of life: workplace, family, and neighborhood.[3] The peer effects are substantial and economically meaningful: On average, one new electric car causes, in the next quarter, an additional .094 new electric car acquisitions in the workplace, .023 in the family, and .22 in the neighborhood. The estimated peer effects for electric cars are considerably stronger than for petrol or diesel cars, highlighting the significance of peer effects of new technologies in the automobile market. The results are robust to alternative functional specifications, sample restrictions, placebo tests, and peer group dynamics.

[1]Social learning has been established as an essential determinant of early technology adoption in numerous economic settings, primarily in developing countries. Agriculture (Foster & Rosenzweig, 1995; Conley & Udry, 2010), deworming programs (Kremer & Miguel, 2007), new crop choices (Bandiera & Rasul, 2006), and fertilizer adoption (Duflo et al., 2011) are a few examples.

[2]I aggregate hybrid electric, plug-in, and battery electric cars into one outcome variable and refer to these as "electric cars" throughout the paper.

[3]The idea that people learn from their peers has been examined in settings ranging from education (Sacerdote, 2001; Graham, 2008; List et al., 2020), consumption behavior (De Giorgi et al., 2020; Bailey et al., 2022), participation in welfare programs (Dahl et al., 2014; Hesselius et al., 2009; Persson et al., 2021; Asphjell et al., 2013), to criminal behavior (Bhuller et al., 2018; Dustmann & Landerso, 2021), and charitable giving (DellaVigna et al., 2012). In the environmental realm, peer effects have been identified in the adoption of solar photovoltaic panels (Bollinger & Gillingham, 2012; Graziano & Gillingham, 2015), hybrid vehicles (Narayanan & Nair, 2013; Heutel & Muehlegger, 2015; Zhu & Liu, 2013; Jansson et al., 2017; Chakraborty et al., 2022), and water conservation (Bollinger et al., 2020).

To address whether the results correspond to a substitution from other vehicle fuel types, I estimate how one new peer electric car influences the adoption of new petrol and diesel cars relative to a peer group that did not receive a new electric car at the renewal threshold. The results show that new electric cars initiated through peer effects pull demand from diesel and petrol cars. This implies that peer effects accelerate the adoption of new electric cars and reduce the demand for competing technologies (such as fossil fuel cars). The estimated peer effects, however, may result from individuals pulling forward planned electric car purchases. I find that peer effects generate persistent shifts in demand for electric cars and do not merely reflect intertemporal substitution. One new electric car increases electric car take-up for six-quarters in the workplace, and four-quarters in the family and persists over the entire horizon in the neighborhood, while peer effects show no sign of turning negative.

Peer effects can influence people's electric car take-up through several mechanisms. I provide evidence for information transmission about leasing contracts, financial incentives, charging infrastructure, and exposure to electric cars. In particular, peer effects are greater for newly leased electric cars, during high subsidy periods, and in neighborhoods with public chargers and single-family homes (as opposed to apartment buildings).[4] In contrast, social reputation concerns do not seem to be a primary driver of the observed peer effects. If the key mechanism driving the peer effects is spreading information, then information campaigns about the costs and benefits of adopting an electric car may be a complementary policy tool to increase electric car diffusion.

The cumulative environmental impact of peer effects extends far beyond the electric car decisions of peers. A new electric car in the peer group may also raise environmental awareness of transportation emissions, shift social norms of driving fossil fuel cars, and enhance preferences for new technologies, which affects individuals' transportation choices.[5] Adding up the different sources of car-related CO_2 emissions, an additional new electric car encourages peers to adopt cleaner non-electric cars, drive less, and reduce the number of owned cars, suggesting that peer effects cause a shift to alternative modes of transportation. The total CO_2 net effect induced through the peer adoption of an electric car equals 4.1% of the average CO_2 emission of an individual, which is due to a 1.1% reduction in the average vehicle emission per kilometer driven, a 2% reduction by driving less, and a 1% reduction in the number of cars. While around half of the decrease in average CO_2 emission is explained by adopting new electric cars, the rest is due to non-adopters choosing cleaner fossil fuel

[4]This relates to a growing literature that tries to understand the economic channels behind peer effects (Dahl et al., 2014; Bursztyn & Jensen, 2015; De Giorgi et al., 2020).

[5]This relates to research on the social consequences of green consumer demand (Nyborg et al., 2006; Delmas et al., 2017), green value formation and transitions (Besley & Persson, 2019, 2023), and interactions between innovation and values (Bezin, 2015, 2019).

cars. The peer effect results are illustrated in Section IV.

To shift the electric car adoption of peers, my identification strategy exploits the fact that many individuals in Sweden lease their cars and replace them on a fixed three-year schedule. Specifically, I use the timing of the leasing contract renewal as an exogenous shock to peer car adoption. Taken alone, the lease timing instrument shifts the adoption of new cars in general, instead of exclusively new electric cars. To isolate exogenous shocks to peers' electric car adoption, I link the timing of the peers' leasing contract renewal with an individual prediction of their probability of adopting a new electric car, which I constructed using machine learning techniques. Notably, the variation in electric car adoption is not driven by differences in the composition of peer groups, as the sum of probabilities to lease a new electric car is controlled for across groups.

To address how policymakers should optimally design subsidies for electric cars, I construct a conceptual framework incorporating how peer effects influence the trajectory of CO_2 emission damages using a discrete choice model of car purchases in Section V. The framework suggests that the subsidy should equal the difference between the lifetime emission damages of fossil fuel and electric cars minus the peer-induced emission changes from fossil fuel and electric cars. The key insight is that the effect of peer influences on the subsidy hinges on the extent to which peer-induced electric cars displace fossil fuel cars. If the peer-induced emission changes from reducing fossil fuel cars exceed the emission changes from additional electric cars, the effect on the subsidy is positive. In contrast, the effect on the subsidy is ambiguous if the peer-induced externality changes from the additional electric cars only partly displace the emissions from fossil fuel cars.

To evaluate how peer effects influence optimal subsidies for electric cars, I combine the estimated peer effects on fossil fuel and electric car adoption with their respective CO_2 emission damages. Peer effects amplify the environmental benefits of electric car adoption, as the emission reductions from displaced fossil fuel cars outweigh the additional emissions from new electric cars. These peer-induced emission reductions amount to \$1,482, leading to an optimal subsidy that is 66.2% higher than a standard Pigouvian subsidy. This higher subsidy not only accounts for the unincorporated externalities of fossil fuel and electric cars but also for the additional emission reductions driven by peer-induced shifts in vehicle adoption.

The literature on peer effects in early technology adoption has evolved along three dimensions. One is related to identifying peer effects, which requires addressing the endogeneity of the peer's behavior. This has proven difficult given the well-known econometric issues of reflection, correlated unobservables, and endogenous group membership (Manski, 1993; Brock & Durlauf, 2001; Moffitt et al., 2001). Recent work studies narrow settings by using distinct visual features or a particular type of car (Toyota Prius) as instruments.[6] Besides these identification issues, a central challenge in studying peer effects is to construct appropriate peer groups and access data that matches members of a peer group. Previous work treated all past adopters in surrounding geographic entities as the reference group, missing out on interpersonal influences along other dimensions. A third challenge is to derive implications for optimal environmental policies in the presence of peer effects. While prior studies have focused on calculating subsidies based on externalities from electric cars (Holland et al., 2016; Rapson & Muehlegger, 2023), the existing research lacks a theoretical framework that characterizes how peer effects alter the optimal incentives setting.

This paper advances the current state of research along all three lines. First, my methodological contribution is to demonstrate how econometric techniques from the recent shift-share instrumental variables (SSIV) literature can be applied to estimate peer effects (Adao et al., 2019; Borusyak et al., 2022), which unlocks a wide range of potential future applications. To address the econometric concerns inherent in measuring peer effects, I link the timing of the leasing contract renewal with a measure of each individual's probability of adopting a new electric car. This identification approach mirrors a shift-share research design that sums up the estimated probabilities (i.e., exposure shares) among all peers at the leasing contract renewal (i.e., shifts). Section III presents the empirical specification to measure peer effects and explains the identification strategy.

To give a concrete example of the identification strategy, suppose that there are two similar peer groups (A and B), each with a single lessee whose contract expires in a given quarter. While the probability that the new car is electric is high for the person in peer group A, it is low for the person in peer group B. The identification strategy then compares the subsequent electric car adoption of other people in the peer group that experienced an expiring car leasing contract by someone who was *ex-ante* predicted to be likely to adopt an electric car (peer group A) relative to a peer group that had someone exposed who was unlikely (peer group B). Consequently, any differences in peer group electric car adoption in the period following the peers' contract renewal are informative about the role of peer effects. The variation in the electric car adoption is determined by which individual in the peer group is randomly induced to the expiring leasing contract, while both peer groups have the same predicted probabilities of adopting a new electric car on average.

[6]The identification strategy in Heutel and Muehlegger (2015) exploits whether initial exposure to a low-quality (Honda Insight) versus a high-quality product (Toyota Prius) affects the likelihood of purchasing a hybrid vehicle. Narayanan and Nair (2013) estimate the peer effect using the adoption of hybrid vehicles that are exact versions of their non-hybrid counterpart (Honda Civic) as an instrument for the network adoption of the Toyota Prius in California. Their identifying assumption is that adopting a hybrid car is not subject to social effects if a virtual identical combustion engine car exists.

Second, I combine several administrative data sets spanning the population of Sweden and all vehicle ownership, purchase, and leasing records to construct peer groups along workplaces, families, and neighborhoods. The final data set consists of a comprehensive list of individual socio-demographic characteristics, peer group characteristics, car attributes, and charging infrastructure variables from 2012 to 2021. This data allows me to study whether peer effects matter for the electric car take-up among co-workers, relatives, and neighbors. Section II summarizes the data set and peer group construction.

Third, I show how government policy – namely environmental subsidies – interacts with peer effects and how this can inform the design of optimal environmental policies. An essential contribution of my theoretical framework is that it delivers formulas for environmental subsidies as a function of emission damages and peer effects that can be estimated in various empirical applications. Specifically, by deriving a modified form of a Pigouvian subsidy, I characterize the optimal subsidies for electric cars in the presence of peer effects. Finally, I discuss how different mechanisms of the peer effects alter the optimal Pigouvian subsidy.

II. Data

A. Data construction

Data sources. The primary data sources are the Swedish vehicle register (*Fordonsregistret*), the longitudinal integrated database for health insurance and labor market studies (*LISA*), the occupational register (*Yrkesregistret*), the population and housing census (*Folk- och bostadsräkningar*), the Swedish business register (*Företagsregistret*), and the geographic database (*Geografidatabasen*) for the period 2012 to 2021 provided by Statistics Sweden. In addition, I merge this data with information on the charging station network and the financial implications of vehicle reforms from the Ministry of the Environment (2011, 2017).

The vehicle register entails data on all vehicles registered by Swedish residents. The register contains information on the car's general status (registration date, whether it is owned by an individual or company, whether it is leased, when the car became the property of the current owner, in use or not, etc.), the vehicle specification (make, model, and trim), characteristics (service weight, odometer reading, fuel type, fuel efficiency, particle filter, emissions, etc.), and the annual vehicle kilometers traveled. Each registration also records a vehicle identification number and a social security number equivalent, which uniquely identifies all individuals in Sweden. The vehicle identification number allows me to track the ownership of vehicles over time.

To match individuals to their cars, I link the vehicle registry through the social security number equivalent to the LISA data, which merges several administrative and tax registers for Swedish individuals aged 18 and above. LISA contains a list of socio-demographic information (such as gender, age, family situation, income, education, and employment status). I supplement the data with the geographic location of the individual's residence, measured by 250m grid cells in all urban and 1000m cells in rural areas. To add occupational status, I link the data to the Swedish occupational register, which includes a unique identifier of the workplace and information on the gross salary, employment status, workplace industry code, and employment duration on an annual basis. Similarly for firms, I add information on Swedish firms using the business register. This includes a set of information on the firm (number of employees, net revenue, personnel cost, and social contribution cost).

The charging infrastructure is supplemented through data from ChargeX (*Uppladdning.nu*). The operators of this website provide free charging information services through map interfaces and app solutions and have collected and maintained Sweden's charging station database since 2008. It includes information on the number of charging points and plug-in spaces by their opening date and location coordinates. Charger characteristics include the operator's name, the connector type and voltage of each outlet, and the charging power.

B. Peer groups

A pervasive challenge in studying peer effects is to construct appropriate peer groups and access data that matches members of a peer group. This comprehensive administrative data allows me to examine whether peer effects matter for adopting electric cars along three dimensions: workplaces, families, and neighborhoods. These groups are a significant source of social influence, as co-workers, relatives, and neighbors engage in frequent social encounters, and their cars are visible to each other.[7]

The first social domain is assumed to be co-workers who work in the same workplace. Because co-workers are more likely to interact directly in small- and medium-sized firms, which account for 40.5% of the workforce, I restrict the co-worker peer group to workplaces with at least 5 and up to 150 employees.[8]

Using the multi-generational register (*Flergenerationsregistret*) that connects individuals to their parents and siblings, I define the family as all first- and second-degree relatives. If a person is adopted, I consider the adoptive parents to be the child's family. A first-degree relative includes the person's parents, (half-)siblings, and children, while second-degree relatives refer to the person's grandparents, aunts, uncles, nephews, and nieces.

[7]For instance, cars are visible to colleagues when parked outside offices and are likely topics of discussion among co-workers (Jansson, 2011; Johansson-Stenman & Martinsson, 2006). In residential neighborhoods, vehicle selection is indicative of the driver's social standing (Johansson-Stenman & Martinsson, 2006).

[8]As some individuals receive compensation from multiple employers, the workplace is the company that pays the greatest annual compensation.

The third social group is the neighborhood. Using the geographic coordinates of residences, I define all individuals living within the same 125m radius in urban and 500m in rural areas as the neighborhood population.[9]

As peer effects are more easily measurable across individuals, I exclude cars owned by legal entities (as opposed to private individuals) throughout the empirical analysis. In addition, I limit the sample to the three most frequently driven cars based on vehicle kilometers traveled per person.

C. Descriptive statistics

Table A1 presents summary statistics of individuals and their cars between 2012 and 2021.[10] Panel A summarizes socio-demographic statistics on the individual-by-year level for Swedes above 18. The average Swede is 47 years old, with around 12 years of education, and earns a disposable family income of 332,670 Swedish kronor (SEK) (≈ \$35,398), conditional on being employed.[11] 56% of individuals are married or live with a cohabitant, 44% have at least one child, and around 41% own at least one car. The sample represents an annual average of 7,947,218 Swedes.

Panel B of Table A1 highlights the descriptive statistics of the Swedish vehicle registry data, which are at the vehicle-by-year level. The average car is 11 years old, travels 11,905 kilometers per year, and emits 122 grams CO_2 per kilometer. The Swedish fleet comprises an average of 3,531,815 private cars.

Table A3 lists the aggregated characteristics of workplaces, families, and neighborhoods between 2012 and 2021. The average individual has 45 co-workers, 7 relatives, and 261 neighbors. The number of new electric cars per peer group, the outcome of interest, equals .75 in workplaces, .09 in families, and 2.28 in neighborhoods. For all panels, the bottom row displays how many people have expiring leasing contracts, which serve as an instrument for new car adoption. The total number of co-workers, relatives, and neighbors at the three-year leasing renewal equals .72 in workplaces, .1 in families, and 3.14 in neighborhoods.

[9]This follows an extensive literature defining networks through geographic entities (Topa, 2001; Arzaghi & Henderson, 2008; Bell & Song, 2007; Manchanda et al., 2008; McShane et al., 2012; Narayanan & Nair, 2013; Kuhn et al., 2011; Agarwal et al., 2021).

[10]Relative to the population and car owners (Table A2), electric car owners are less likely to be unemployed and more likely to be male, educated, married, and wealthier. Notably, electric car owners have, on average, one additional year of education and earn SEK 146,000 (≈ \$15,120) more in annual gross salary than the average Swede.

[11]I convert SEK to US dollars using the exchange rate from January 1, 2020 (\$.1063/SEK).

D. Swedish car market

Evolution of alternative fuel cars. Historically, the Swedish vehicle fleet mainly consisted of cars that run on petrol or diesel. Since 2006, however, alternative fuel cars have gradually penetrated the Swedish market. Figure 1 displays the number of new cars registered monthly by individuals for each alternative fuel type between 2006 and 2021. Between 2006 and 2010, the registrations of ethanol-powered cars increased rapidly in Sweden, making them the first alternative-fuel type to reach the market.

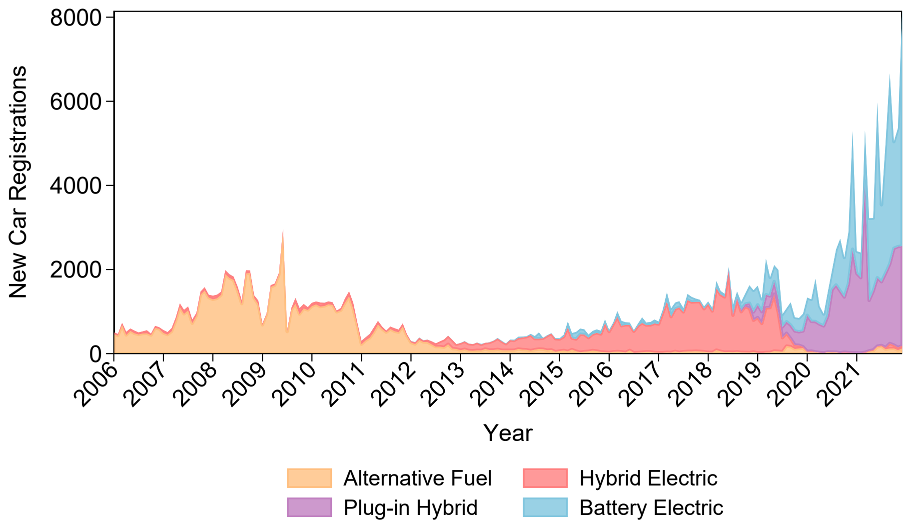

Figure 1: New registrations of alternative fuel cars

Notes: The figure displays the number of monthly new car registrations of alternative fuel cars that were registered by private individuals in the Swedish vehicle market between 2006 and 2021. Alternative fuel cars are vehicles that partly or fully run on alternative fuels such as ethanol, compressed natural gas (CNG), or LPG. A hybrid electric car combines a conventional internal combustion engine with an electric propulsion system, using the engine to charge the battery while driving. A plug-in hybrid electric car can be recharged from an external source of electricity and another fuel to power an internal combustion engine. A battery-electric car is powered by one electric motor that only runs on electricity from a battery.

The uptake of electric, plug-in, and hybrid electric cars began around 2012. Since there has been a steady increase in sales of electric cars annually, from 1,221 units in 2012 to 55,270 in 2021. This equals a 38.1% market share of electric cars relative to all new registrations in 2021. Electric cars sold were evenly distributed among the fuel types, with hybrid electric cars accounting for 36% of new electric cars and battery-electric and plug-in hybrid electric cars representing 28.7% and 35.3%, respectively. In total, private individuals have registered 149,184 electric cars since 2012.

Leasing market. The Swedish automobile market has two striking features that I exploit to identify peer effects. First, a substantial portion of new cars is leased (as opposed to purchased). The share of newly leased cars relative to the total number of new car registrations in Sweden has increased from 5% in 2012 to 49.6% in 2021 (Figure A1). Low interest rates are one explanation for the large proportion of leased cars. As the taxable vehicle fringe benefits are calculated as a percentage of interest rates, low interest rates reduce the leasing cost (Appendix B.2).

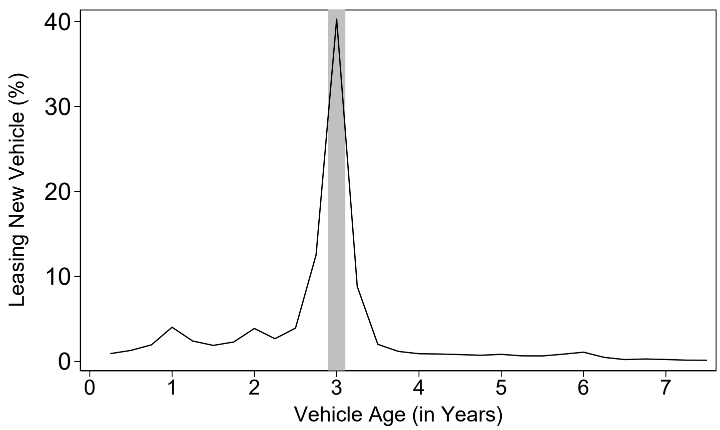

Figure 2: Leasing contract renewal probability

Notes: The figure illustrates the contract renewal probability of leased cars with respect to the time in the current car contract (i.e., quarters since first registration).

Second, leasing contracts typically have a fixed three-year schedule. First introduced by Volvo in the late 1960s, car manufacturers in Sweden typically offer a warranty for the first three years on new cars. Since then, car leasing contracts have been set up for this period. To validate this timing in leasing renewal, Figure 2 plots the probability of leasing a new car against the number of quarters since the current leased car's registration. The probability of leasing a new car spikes when the current car age crosses the three-year threshold (the gray area). More than 40% of leased cars are replaced exactly 12 quarters after their first registration. Given the large market for newly leased cars and the fact that around 40% of these leased cars are exchanged after precisely three years, the timing of peer's leasing contract renewal reflects exogenous timing in the take-up of new cars.

III. Empirical methodology and identification

A. Peer effect specification

To empirically estimate the size of peer effects for electric cars in the Swedish vehicle market, the equation of interest (1) is given by a regression of whether individual i adopts a new electric car in quarter q on the number of newly registered electric cars in the previous quarter q_{-1} in peer group p, conditional on all individual and peer group characteristics:

$$V^e_{i,q} \;=\; \alpha + \;\theta^e V^e_{p-i,q-1} + \;\gamma \overline{X}_{p-i,q} \;+\; \delta X_{i,q} \;+\; \phi_q \;+\; \varepsilon_{i,q}, \tag{1}$$

where i indexes the individual, p the peer group of size N_i excluding individual i, q the quarter and superscript e indicates electric cars. In all notations, attributes specific to a vehicle are shown as superscripts, while characteristics specific to an individual are shown as subscripts. The dependent variable, $V^e_{i,q}$, is an indicator of whether individual i acquires a new electric car in quarter q. The peer influence variable equals the sum of all electric car registrations per peer group in the previous quarter q_{-1} excluding individual i: $V^e_{p-i,q-1} = \sum_{j\epsilon N_i, j\neq i} V^e_{j,p,q-1}$. The vector $X_{i,q}$ represents a rich set of individual demographic variables, residential charging infrastructure, and previous car attributes.[12] To control for the underlying peer group characteristics, $\overline{X}_{p-i,q} = \sum_{j\epsilon N_i, j\neq i} \frac{X_{j,q}}{N-1}$ includes the average characteristics of the peer group using the same set of demographic variables excluding individual i. The quarter fixed effect ϕ_q captures time-varying factors such as nationwide incentives for cars, gas price shocks, or the introduction of a new model. $\varepsilon_{i,q}$ captures individual i's error term.

The "per capita" peer coefficient θ^e measures the effect of the number of new electric cars in the peer group in the previous quarter ($V^e_{p-i,q-1}$) on whether the person adopts a new electric car in the current quarter ($V^e_{i,q}$). The "total" peer group measures how adopting one new electric car influences the total number of new electric cars in the peer group in the next quarter.

This empirical specification makes two implicit assumptions: First, it assumes a lag of up to one quarter in the transmission of peer effects. Second, it assumes a linear-in-sums model such that peers are influenced by the total number of new car registrations in peer groups while controlling for the number of peers.[13] An alternative functional form models

[12]The individual demographic control variables include age, gender, disposable family income, gross salary, employment status, a self-employment dummy, being married or cohabiting with a partner, having at least one child, years of education, commuting distance, number of peers, and being at the lease renewal. The residential charging infrastructure captures the installation of a charging point, the number of plug-ins and charging stations, charging time, and charging capacity. The previous vehicle and driving attributes account for vehicle kilometers traveled, owning an alternative fuel or electric car, the total number of cars, emissions, engine power, service weight, and fuel efficiency averaged over the previous year.

[13]Controlling for network size in a linear-in-sum model is crucial as people with more friends are more

peer effects as the share of peers who acquired new electric cars (linear-in-means). The results are robust to this alternative functional form (Table E1) and varying transmission time of peer effects (Table E2).

B. Shift-share IV design

The main empirical challenge is to disentangle the causal relationship of peer influence on electric car adoption from the exogenous and correlated effects. A successful instrument needs to be as good as randomly assigned ("independence") and shift the electric car adoption probability of an individual's peer ("relevance") without influencing the car decision through any other channel than the peer effect ("exclusion restriction"). To construct an instrument that meets these requirements, I link the timing of the leasing contract renewal (as an exogenous shock to the car take-up) with a measure of each individual's probability of adopting a new electric car. This identification strategy corresponds to a shift-share (or Bartik) research design (Adao et al., 2019; Borusyak et al., 2022),[14] where the exogenous component comes from the timing of expiring individual-level car leasing contracts and the non-random exposure shares from heterogeneity in the adoption probability of electric cars at the renewal threshold.[15]

Intuition for identification. To conceptualize how the identification strategy measures peer effects, assume that there are two similar peer groups, and we want to measure how the car choices of peers influence the individual in the red dashed circle (Figure 3). Each peer group contains four peers, two of whom have a high probability of adopting an electric car (green), and two have a low probability (brown). Suppose that in a given quarter, the lease contract for one individual in each group expires. While the lease expires for someone unlikely to adopt an electric car in the top peer group, it expires for someone likely to go for an electric car in the bottom peer group. The identification strategy compares the subsequent electric car adoption in the peer group that experienced a leasing renewal by someone who was *ex-ante* predicted to be likely to adopt an electric car relative to a peer group that had someone exposed who was unlikely. Consequently, any differences in peer group electric car adoption in the period following the lease renewal are informative about

frequently exposed to peer effects (Bramoullé et al., 2020).

[14] The shift-share design has been used in numerous settings, such as firms that are differentially exposed to foreign market shocks (Hummels et al., 2014; Berman et al., 2015), immigration shocks (Tabellini, 2020; Fouka et al., 2021; Derenoncourt, 2022), individuals facing different national income trends (Boustan et al., 2013), or countries that are differentially exposed to the U.S. food aid supply shocks (Nunn & Qian, 2014).

[15] The recent literature on shift-share instruments stresses two separate paths for identification: exogenous shocks versus exogenous shares. As individuals are not randomly choosing electric cars at the renewal threshold, I leverage exogenous variation from the timing of the leasing contract renewal, while allowing the variation in exposure shares to be non-random.

the role of peer effects. The variation is not driven by differences in the composition of the peer groups as the sum of people adopting a new electric car among leasers is identical across groups; instead, the renewal timing selects different people to lease a new electric car.

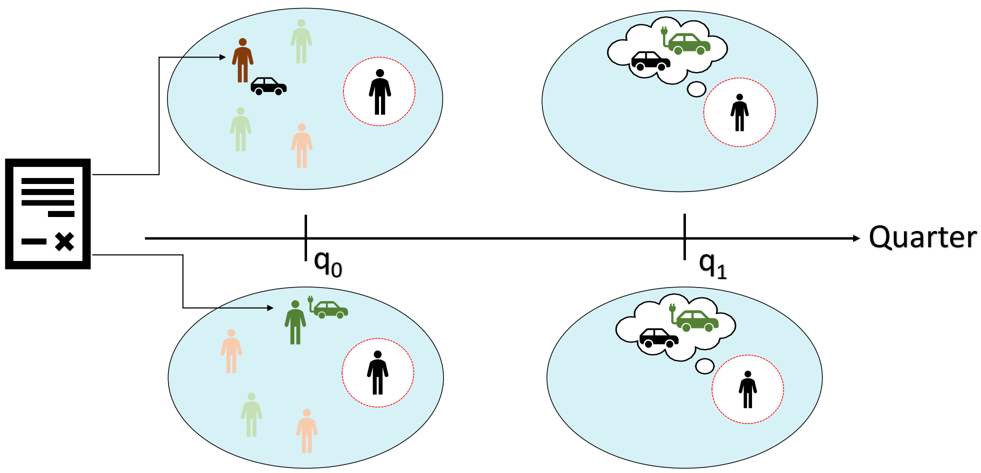

Figure 3: Intuition for identification strategy

Leasing contract renewal. The exogenous component of the SSIV-design is based on the idea that car leasing contracts are frequently renewed, and cars are exchanged after three years in the Swedish vehicle market. The exogenous variation exploits the timing of the leasing renewal contract as an exogenous shock to the peer car adoption.[16] This instrument, however, would shift the adoption of all general cars instead of exclusively electric cars. Hence, I do not solely use how many peers are at the contract renewal in a given quarter but also the type of peers and their likelihood of buying electric cars.

Electric car adoption propensity. To operationalize a research design that only shifts peer electric car adoption, I interact the leasing contract renewal with a measure of each individual's probability of adopting a new electric car at the contract renewal.

For the non-random exposure shares, I develop a measure of each individual's probability of adopting a new electric car. I view the estimation of whether the individual at the leasing renewal adopts an electric car as a pure prediction problem, which follows a growing literature that proposes to use machine learning estimation to fit the first stage in an instrumental variable context when the number of instruments is large (Belloni et al., 2014; Mullainathan

[16]The growing number of leasing contract renewal shocks over time does not pose a possible concern (Figure A1). However, as long as the shocks demonstrate idiosyncratic variation in the type of person at the contract renewal while controlling for the number of leasing renewals, the validity of the instrument remains even if the number of shocks in peer groups increases.

& Spiess, 2017; Peysakhovich & Eckles, 2018; Athey, 2018; Chernozhukov et al., 2018). Under the assumption that the peer contract renewal timing is random, the type of peer facing this renewal must also be plausibly random. In this context, I use information about individual demographics, peer group characteristics, charging infrastructure, and past car attributes (summarized as X) to estimate a single propensity of adopting a new electric car for each individual who leases a three-year-old car.[17] As the relationship between the features and the demand for electric cars is likely to be complicated and non-linear, I fit a neural network in equation (2) to predict these propensities:

$$\widehat{Pr}(V^e \mid V^{3y}_{i,q} = 1)_{i,q} \;=\; g_\vartheta(X_{i,q}). \tag{2}$$

The function g_ϑ represents the neural network, parameterized by weights ϑ, that maps covariates $X_{i,q}$ to predicted adoption probabilities through learned nonlinear transformations. To avoid overfitting and ensure out-of-sample validity, the propensity estimation employs cross-validation, whereby the neural network is trained and evaluated on separate samples. Appendix C.1 provides details on the design and performance of the neural network. For estimation consistency, the predicted propensity must be on average an unbiased estimate of the true probability of electric vehicle adoption at the renewal cutoff, while improved predictive accuracy enhances the power of the first-stage estimation. Figure C1 shows that the predicted and true probabilities of electric vehicle adoption closely align with the 45-degree line, indicating that the neural network accurately captures individuals' actual take-up behavior at the renewal cutoff. Figure C2 confirms that the predictive accuracy of the estimated propensities is high. I use the neural network as it provides the best fit between predicted and actual propensities, while results are robust to alternative machine learning techniques (Table E3).

To give concrete examples, Figure 4 plots the probability of adopting an electric car at the renewal threshold for four characteristics: years of education, annual salary, vehicle usage, and the previous engine power. Panel A indicates that the probability of adopting an electric car at the lease renewal for people with less than 12 years of education is around 3%, while it amounts to over 10% for people with a Ph.D. For salary, we observe a high adoption probability for top-income groups in Panel B. Furthermore, the adoption probability of electric cars is inversely related to the vehicle's traveled kilometers. Finally, a car owner with a smaller previous engine generally relates to higher electric car adoption. I predict a single propensity using the heterogeneity of these rich background characteristics.

[17] For the remainder of the paper, I refer to these as "propensities."

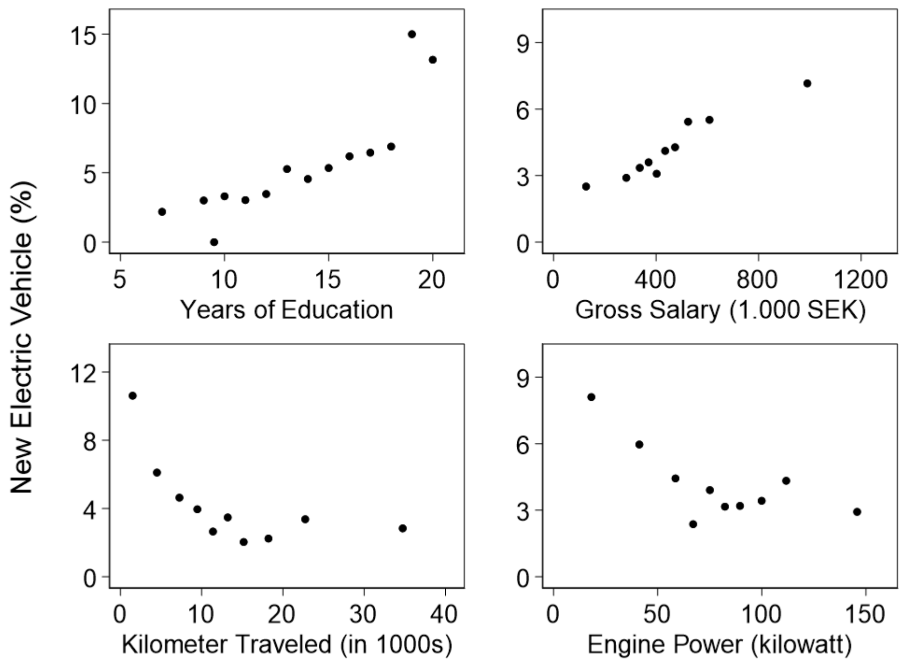

Figure 4: New electric car probability by demographic characteristics

Notes: The figures illustrate the probability of leasing a new electric car at the three-year leasing contract renewal for four different characteristics: Years of education (Panel A), gross salary in thousand SEK (Panel B), annual vehicle kilometers traveled (Panel C), and previous engine power in kilowatt (Panel D).

C. Estimating equations

To construct the SSIV for the adoption of electric cars in peer groups, I interact a dummy indicating if the individual is at the three-year contract renewal ($V^{3y}_{j,q-1}$) with the individual's estimated propensity ($\widehat{Pr}(V^e \mid V^{3y}_{j,q-1} = 1)$). The exogenous variation comes solely from the interaction of these two terms but not from the number of peers at the contract renewal or their propensities. The instrument then equals the sum of all propensities across all peers at the three-year leasing renewal threshold in a given quarter.[18] The first stage (3) and reduced form equation (4) of the SSIV can be implemented by the following two-equation system:

$$\begin{aligned} V^e_{p-i,q-1} \;&=\; \alpha^e \sum_{j \epsilon N_i} V^{3y}_{j,q-1} \cdot \widehat{Pr}(V^e \mid V^{3y}_{j,q-1} = 1) \;+\; \delta X_{i,q} \;+\; \gamma \overline{X}_{p-i,q} \;+\; \phi_q \\ &+\; \delta_1 V^{3y}_{p-i,q-1} \;+\; \delta_2 \overline{Pr}(V^e \mid V^l_j = 1)_{j,q-1} \;+\; u_{i,q-1} \end{aligned} \tag{3}$$

[18]This can be interpreted as an instrumental variable regression that uses the propensity-weighted sum of peer contract renewal as shocks (Borusyak et al., 2022).

$$
\begin{aligned}
V^{e}_{i,q} \;=\; & \beta^{e} \sum_{j \epsilon N_i} V^{3y}_{j,q-1} \cdot \widehat{Pr}(V^{e} \mid V^{3y}_{j,q-1} = 1) \;+\; \delta X_{i,q} \;+\; \gamma \overline{X}_{p-i,q} \;+\; \phi_q \\
& +\; \delta_1 V^{3y}_{p-i,q-1} \;+\; \delta_2 \overline{Pr}(V^{e} \mid V^{l}_{j} = 1)_{j,q-1} \;+\; u_{i,q-1}.
\end{aligned} \tag{4}
$$

The average of the estimated propensities is not constant across peer groups, placing the SSIV in the "incomplete shares" class with panel data (Borusyak et al., 2022). To control for the composition of peer groups and their car preferences, I add two key control variables that capture these differences in propensities across peer groups. First, I additionally control for the number of contract renewals in each peer group in a given quarter ($V^{3y}_{p-1,q-1}$). Second, I add a control for the average propensity to lease a new electric car for all leasing peers (l) within a peer group ($\overline{Pr}(V^{e} \mid V^{l}_{j} = 1)_{q-1,j}$). This accounts for a potential direct relationship between the average peer group probability and the individual probability of adopting a new electric car in a given quarter. This follows the recent shift-share literature (Borusyak et al., 2022) to control for the sum of the exposure shares when the sum varies across groups.

Identifying assumptions and validity checks. Validity of the SSIV requires two assumptions to be fulfilled: instrument validity and instrument relevance. The strength of the instrument is verified in Figure 5. The exclusion restriction can be stated as follows:

$$
E\left[\sum_{i} \Big(\sum_{j \epsilon N_i} V^{3y}_{j,q-1} \cdot \widehat{Pr}(V^{e} \mid V^{3y}_{j,q-1} = 1)_j\Big) \cdot \varepsilon_i \mid X_{i,p_{-i}}\right] \;=\; 0. \tag{5}
$$

Equation (5) expresses that propensity-weighted shocks and the error term are orthogonal. This is satisfied as long as the shocks are as-good-as-randomly assigned, mutually uncorrelated, large in number, and sufficiently dispersed in terms of their average exposure, conditional on the control vector. Applied to this context, the propensity-weighted number of peers at the leasing renewal must be orthogonal to omitted characteristics that are correlated with the individual electric car adoption, after conditioning on the specified baseline characteristics. Although this assumption is inherently untestable, I examine the plausibility of the many conditionally uncorrelated shocks assumption by analyzing the distribution of shocks and using balance tests to corroborate the plausibility of the conditionally exogenous shock assignment assumption (Appendix C.2).

One possible concern is that the timing of leasing contract renewal is correlated among peers, resulting in re-occurring simultaneous car decisions in the absence of any peer effects. To address such concerns, I directly control for whether the person is in the car leasing renewal quarter such that the variation purely stems from the leasing renewal of peers. In addition, I document that my findings are robust to peer groups with exactly one lease renewal, suggesting that correlated lease contracts do not influence the peer effects (Table E1). To further mitigate potential concerns regarding disparities between peer groups with and without leasing peers, restricting the sample to peer groups that experienced at least one leasing renewal leaves the peer effects unaltered. Finally, including fixed effects over which peers are defined has no impact on the estimated peer effects.

As a validity check, I also test the results for placebo peer groups. The placebo co-workers are: 1. Firm-level co-workers: These are co-workers employed in the same firm, two-digit industry, and municipality, but they do not work in the same plant; 2. Future co-workers and neighbors: This placebo peer group consists of future co-workers or neighbors that sort into the individual's workplace or neighborhood. Table E4 verifies that there are no peer effects among placebo co-workers and neighbors.

Under the assumption that the instrument is orthogonal to all observed and unobserved covariates, this research design addresses the three main concerns that arise in the identification of endogenous peer effects: reflection, endogenous group membership, and correlated unobservables. It solves the reflection problem by using lagged, but not contemporaneous, adoption by peers (Towe & Lawley, 2013; Bollinger & Gillingham, 2012; Bailey et al., 2022). As peer groups are determined before the exogenous shock, endogenous group membership does not pose a threat to the identification.[19] Peer group changes that happen after the exogenous shock are either the causal result of the instrument or orthogonal to it. Correlated unobservables also do not bias the peer effect estimates as the timing of peers' lease renewals provides quasi-random variation that is independent of unobserved factors influencing individual car adoption decisions.[20]

Inference. In the case of shift-share instruments, standard inference procedures lead to standard errors that are too small if they are correlated across observations similarly exposed to the same set of shocks.[21] To account for a potential correlation between residuals across individuals with similar propensities in peer groups, I follow the statistical inference procedures of the recent shift-share literature that suggests clustering standard errors on

[19]For instance, family-friendliness is a driver of women's employment decisions (Herr & Wolfram, 2009; Goldin & Katz, 2012), and if, at the same time, family-friendliness is related to the car purchasing decision, this may increase the electric car adoption within the workplace in the absence of any peer effects. However, this does not threaten identification because workplace composition—including characteristics such as family-friendliness—is predetermined and thus fixed prior to the timing of the exogenous lease renewal shocks that generate identifying variation.

[20]For example, targeted marketing campaigns within neighborhoods or vehicle fleet policy changes in the workplace may influence car take-up within the peer group as a whole, but they are unlikely to be correlated with whether the individual whose lease expires happens to have a higher ex-ante propensity to adopt an electric car after conditioning on our set of control variables.

[21]This relates to Moulton's (1986) standard error clustering problem, in which the residual and the instrument are correlated across observations within predetermined clusters. In the presence of SSIV, there is the additional complication that every pair of observations with overlapping shares may be correlated.

the shock-level, which accrues to peers in this context (Adao et al., 2019). In the non-overlapping workplace and neighborhood, I cluster standard errors at the group over which peers are defined. In the family, however, I cannot cluster standard errors at the peer-group level due to the overlapping network structure. Hence, I explore the robustness of my statistical inference to various approaches of constructing standard errors (Figure C3). To account for the most possible across-individual dependencies in the error term, I cluster the standard errors on the individual-level in the family.[22] Appendix C.3 discusses statistical inference and standard error construction.

First stage results. To provide evidence for the relevance of the instrument, Figure 5 displays the point estimates and 95%-confidence intervals of the first stage equation (3) for all three peer groups. The x-axis is the value of the shift-share instrument, which I group into 10-percentile bins. The y-axis plots new peer electric car adoption, residualized on the full set of baseline controls and quarter-fixed effects. The first stage estimates α^e corroborate that a predicted increase of one percentage point in leasing a new electric car translates into 1.37 new electric cars in the workplace, 1.05 new electric cars in the family, and 2 new electric cars in the neighborhood. This implies that one additional person with an expiring leasing contract predicted to adopt an electric car results in approximately 1 to 2 additional new electric cars in that peer group in the same quarter.[23] The first stage F-statistics for the workplace (350.6), family (10,683.4), and neighborhood (368.8) exceed the conventional threshold values for instrument relevance.

How to interpret treatment effect estimates. The identification strategy compares the electric car adoption of two peer groups, where one peer group received a new electric car (i.e., the treatment group) relative to a peer group that did not receive a new electric car at the renewal threshold (i.e., the control group). Instead, the control group either acquires a new petrol or diesel car or does not renew the leasing contract; in this case, the individual either retains the three-year-old car or returns it. On average, 63% to 65% of individuals in the control group do not adopt a new car at the three-year threshold, whereas 31% to 33% lease a new petrol and 4% a new diesel car. Hence, the peer coefficient must be interpreted relative to the subsequent electric car adoption of a peer group in which about two-thirds of contract renewals result in no new car adoption, and one-third in either a new petrol or diesel car. I assess the stability of the peer effect coefficient relative to different control groups and find that it remains robust when using control groups that either do not renew

[22]Although the presence of across-cluster links implies that there remains the potential for correlations in the error terms, I document that standard errors are not influenced by dependencies in larger peer groups.

[23]One reason the first stage coefficient is larger for neighborhoods than for workplaces and families is the higher compliance with expiring lease contracts in neighborhoods. One additional person at the renewal threshold adds .39 new cars in the workplace, .33 in the family, and .42 in the neighborhood (Figure E1).

their lease or instead adopt a new fossil fuel car (Table E1).

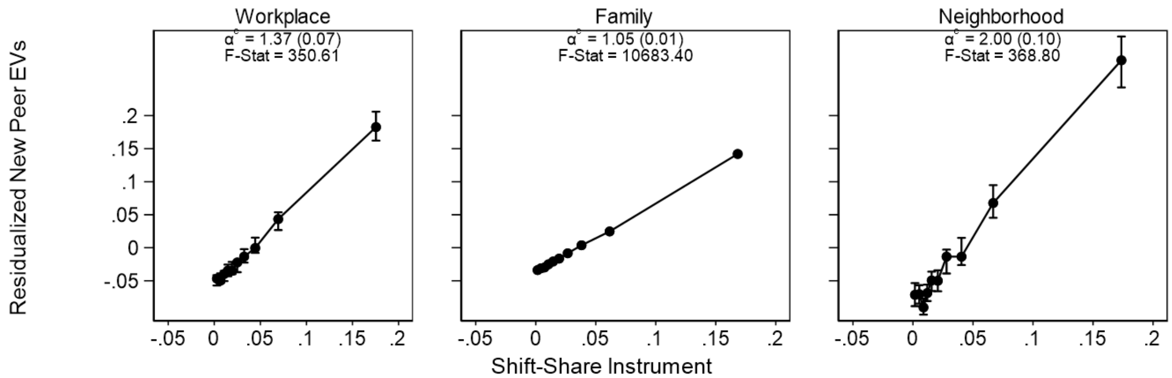

Figure 5: First stage binned scatterplots

Notes: The figures present binned scatterplots of the first stage in the workplace (Panel A), family (Panel B), and neighborhood (Panel C) (using the Stata package binsreg). The shift-share instrument along the x-axis is defined as the interaction between the number of peers at the three-year car leasing contract renewal and their propensities to adopt an electric car. The shift-share instrument is grouped into 10 bins (10 percentiles each) for all groups that experienced a contract renewal in a given quarter. Both relationships are residuals of the set of control variables in equation (1): individual-demographic variables, peer group characteristics, charging infrastructure, peer group demographic control variables, past car choices and quarter-fixed effects. The slope coefficients α^e and the standard errors come from the first stage regression in equation (3). The first stage F-statistics are derived from a peer group level IV regression of the residualized number of new peer electric cars on the propensity-weighted number of expiring peer leasing contracts.

IV. Main Results

A. Regression results

Table 1 reports estimates of peer effects on new electric cars by co-workers (Panel A), relatives (Panel B), and neighbors (Panel C). The coefficients in columns (1) and (2) indicate how adopting one new electric car influences the total number of new electric cars in the peer group in the next quarter. In column (3), I divide those total effects by the size of the peer group, which gives an estimate of the peer effect "per capita."[24] These coefficients imply how one new peer electric car affects the electric car adoption of one co-worker, relative, or neighbor in the next quarter.

The 2SLS estimates indicate strong evidence for peer effects. The peer coefficient in column (2) can be interpreted as follows: On average, one new electric car causes, in the next quarter, an additional .094 new electric car acquisitions in the workplace, .023 in the

[24]The average person has 45 co-workers, 7 relatives, and 261 neighbors (Table A3).

family, and .22 in the neighborhood. One new electric car increases the baseline probability that a co-worker, relative, or neighbor adopt a new electric car by 9.8%, 103.6%, and .8%, respectively. Put differently, approximately one in 10 electric cars in the workplace, 29 in the family, and 4 in the neighborhood trigger a subsequent electric car adoption in the following quarter due to peer effects.[25]

Although the peer effects are largest in the neighborhood in absolute terms, column (3) indicates that the peer effects per co-worker and relative are larger than those per neighbor. Specifically, each new electric car causes, in the next quarter, .0032 new electric cars per relative, and .0021 per co-worker, while the peer effect is .0009 per neighbor. One explanation is that the ties among relatives and co-workers are closer than among neighbors. Another explanation is that estimates in overlapping peer groups, such that co-workers may reside in the same neighborhood or are related, capture potential interdependencies across groups.[26]

The observed peer effects, however, may be present for new cars in general. To identify peer effects for new cars (rather than solely electric cars), I use the leasing contract renewal as an instrumental variable for adopting new cars. In comparison, the peer effects for new electric cars are considerably stronger than for all new cars (Table E5), suggesting that peer groups are more relevant for adopting new, early technologies such as electric cars.

The second stage estimates exceed the OLS estimates in all peer groups. This is surprising, as we expect an upward bias due to similar preferences, facing similar environments, or experiencing common shocks of peer groups. The most likely explanation is that the SSIV estimates represent a local average treatment (LATE) for the subset of people with peers at the lease renewal. Relative to the average population, people leasing cars differ in demographic and vehicle characteristics.[27] Consequently, the observed peer effects with frequent contract renewals may be higher than the average peer effect in the population. Given the high prevalence of leased cars, especially among individuals likely to be early adopters of electric cars, the LATE corresponds to the population we expect to be most influential early

[25]Most relatedly, Narayanan and Nair (2013) estimate that 100 Toyota Prius in the zip code result in one incremental purchase through peer effects. Given the arguably stronger ties of co-workers, relatives, or immediate neighbors (relative to previous adopters in large geographic groups), the observed peer effects are considerably larger than the prior estimates for hybrid EVs.

[26]To test this, I evaluate each peer group independently by subtracting members of other peer groups from the reference group. For example, I exclude relatives working at the same plant (e.g., family-owned businesses). The findings reveal that the workplace and neighborhood effects diminish marginally, while the family effect shrinks by 25% (Table E1). A fraction of the peer effect in families is caused by co-workers or neighbors who are relatives.

[27]Compared to the population, people who lease cars are relatively younger, more likely to be male, more wealthy, less likely to be unemployed, and more likely to be married or cohabitant. An individual leasing a car earns, on average, around 130 SEK (≈ $13,819) more gross salary income and has .75 years more education. Generally, leasers own more fuel-efficient cars, have smaller engines, lower vehicle emissions, and are more likely to be electric.

Table 1: Peer effects in electric car adoption

	OLS	Second Stage	
	(1)	(2) Total	(3) Per Capita
A.Workplace Network			
New Peer Electric Car	.0455***	.0944***	.0021***
	(.0073)	(.0235)	(.0005)
%-Effect	4.7	9.75	9.75
Mean Dep. Variable	.021	.021	.021
B.Family Network			
New Peer Electric Car	.0091***	.0234***	.0032***
	(.0005)	(.0082)	(.0011)
%-Effect	40.42	103.59	103.59
Mean Dep. Variable	.003	.003	.003
C.Neighborhood Network			
New Peer Electric Car	.0371***	.2240***	.0009***
	(.0024)	(.0295)	(.0001)
%-Effect	.13	.78	.78
Mean Dep. Variable	.109	.109	.109

Notes: This table presents the regression estimates of peer effects in workplaces (Panel A), families (Panel B), and neighborhoods (Panel C). Column (1) presents OLS estimates from the regression in equation (1), column (2) and (3) reflect the second stage estimation using the shift-share instrument. The dependent variable in columns (1), and (2) indicates the number of new electric cars in the peer group in a given quarter. The dependent variable in column (3) divides the total effects by the size of the peer group, which gives an estimate of the peer effect "per capita." All regressions include individual demographic, past car attributes, charging infrastructure, peer group demographic control variables, and quarter-fixed effects. The %-effects and the mean dependent variables are reported below the coefficients. The unit of observation is individual×quarter. The time period reaches from 2012 until 2021. Robust standard errors, clustered by plants in Panel A, individuals in Panel B, and neighborhoods in Panel C, are in parentheses. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

in the adoption process.

To identify the characteristics of socially influential individuals, I explore the heterogeneity in the transmission of peer effects in Figure E2.[28] Understanding the heterogeneous patterns in peer effects is valuable for policymakers to predict future adoption rates and target financial incentives toward socially influential groups, which aligns with a large development literature that emphasizes targeting key individuals within social networks to facilitate the diffusion of new technologies (Banerjee et al., 2013). The results indicate that age, education, income, and peer group size are predictors of the strength of peer effects. In particular, peer effects of adopting a new electric tend to be stronger among younger individuals (< 45) and are substantially larger for those with a college degree within families and neighborhoods. In addition, peer effects are amplified in smaller peer groups and increase with income in workplaces and neighborhoods.

B. Substitution

An important question is whether the observed peer effects correspond to newly generated demand or are pulled from other vehicle fuel types. These coefficients are crucial for determining optimal subsidies in Section V, as they quantify the extent to which peer-induced electric car adoption displaces fossil fuel cars. To answer this, I measure how a new peer's electric car adoption influences the subsequent adoption of three fuel types (petrol, diesel, and electric) and new cars. Empirically, I regress whether individual i adopts a new electric, petrol, diesel, and any new car on the number of newly registered electric cars in the previous quarter in the respective peer group.

Figure 6 illustrates the peer effect estimate of one additional new peer electric car on new petrol, diesel, electric, and new cars in each peer group. The top bar in each panel (mirroring the results in Table 1) indicates that an additional peer electric car increases the probability of adopting an electric car in the next quarter. However, the peer electric car adoption simultaneously reduces the probability of adopting new diesel and petrol cars in all peer groups. This suggests that peers do not only accelerate the adoption of electric cars but also displace the adoption of diesel and petrol cars. Hence, the take-up of new technologies accelerates future adoption through positive peer effects and reduces the acquisition of old technologies (such as fossil fuel cars).

Overall, the peer adoption of electric cars results in a reduction of new cars in workplaces and families, but has no impact on new cars in neighborhoods relative to a peer group that

[28] To analyze heterogeneity in peer effects by socio-demographic characteristics, I partition peers into mutually exclusive and exhaustive groups G (e.g., by age, education, income, or group size) and estimate subgroup-specific peer effects by restricting both the instrument and outcome to peers meeting each condition $g \in G$.

does not receive an exogenously-arriving new electric car. This suggests that peer effects in neighborhoods displace fossil fuel cars as the incremental demand for electric cars is pulled from diesel and petrol cars. In workplaces and families, the additional demand for electric cars is more than offset by reduced demand from fossil fuel cars, indicating that peer effects may encourage a transition to other modes of transportation in addition to the displacement of petrol and diesel cars.[29]

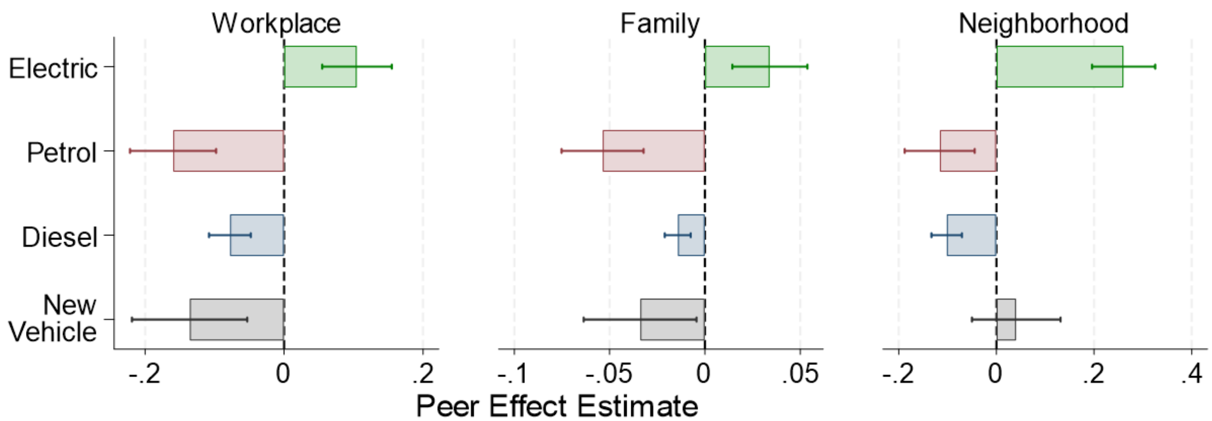

Figure 6: Peer effects by vehicle fuel types

Notes: The plots present regression estimates of peer effects across three different motor fuel types (petrol, diesel, and electric) and all new car registrations for the workplace (Panel A), family (Panel B), and neighborhood (Panel C). The dependent variable measures the number of new petrol (red), diesel (blue), electric (green), or any new cars (grey) in the peer group. All regressions include individual demographic, past car attributes, charging infrastructure, peer group demographic control variables, and quarter-fixed effects. The unit of observation is individual×quarter. The time period reaches from 2012 until 2021. 95%-confidence intervals reflect robust standard errors, clustered by plants in Panel A, individuals in Panel B, and neighborhoods in Panel C.

As we have so far only considered peer effects among the aggregate of all types of electric cars, an important question is how the peer effects of early new technologies (hybrid cars) influence the adoption of later, cleaner technologies (plug-in electric cars). Among the types of electric cars, peer effects are primarily driven by plug-in electric cars (i.e., plug-in hybrid and battery electric). In contrast, new peer hybrid cars displace the adoption of plug-in electric cars (Table E6),[30] which suggests hybrid cars could potentially hinder the transition towards plug-in electric cars.

Conversely, the peer adoption of new fossil fuel (petrol or diesel) cars does not affect the

[29]As the share of peer-owned electric cars in neighborhoods is lower than in workplaces and families, one explanation for the lower rate of substitution within neighborhoods is that peer effects displace fossil fuel cars with higher levels of peer electric car adoption.

[30]This mirrors results in the market for efficient lighting (Armitage, 2022), where early improvements in lighting efficiency (halogens, CFLs) led to reduced adoption of later, high-efficiency products (LEDs).

subsequent adoption of new fossil fuel cars among co-workers and neighbors and has positive effects among relatives.[31] However, it results in a reduction of new electric cars relative to a peer group that experienced a new peer electric car adoption in all peer groups (Table E9). This implies that the peer effects in fossil fuel cars are less relevant for their subsequent adoption in peer groups and displace the adoption of electric cars.

C. Dynamics

Having estimated the peer effects after one quarter, I next explore the dynamics of peer effects over longer periods. This answers how long the social influence of the peer electric car adoption lasts and whether these peer effects generate additional demand for electric cars or merely reflect an intertemporal substitution of already planned future purchases.

Interpreting longer-horizon peer effects becomes more complicated as second-degree effects gradually emerge. For example, an individual's new electric car in quarter q may affect a mutual peer's acquisition in quarter $q+1$, influencing another peer's purchasing decision in quarter $q+2$. The estimated LATE coefficients capture both the direct effect of the initial peer acquisition and all higher-order indirect effects by common peers caused by the initial electric car adoption. Section D.1 documents the regression specifications to estimate the peer effects dynamics.

Figure 7 displays the total peer effect coefficients (θ^e_τ) four quarters prior and up to eight quarters following the peer electric car adoption in quarter $q = -1$ across the three peer groups. The dashed line refers to the peer electric car adoption period, which resembles the first stage regression corresponding to equation (3). Although the parallel trends assumption is inherently untestable, the trends in electric car adoption before the leasing renewal quarter for a peer group that received a new electric car and a peer group that did not receive a new electric car at the renewal threshold suggest that the assumption is likely to hold. The absence of pre-trends in adoption prior to the renewal quarter indicates that anticipatory discussion (e.g., such as peers announcing their intention to buy an electric car when their lease expires) are unlikely to generate reverse causality.

The dynamics reveal that the peer effects of electric cars in neighborhoods persist over the entire horizon, whereas peer effects last for the first six quarters in the workplace and four quarters in the family.[32] After that, the total peer effect converges toward zero. Importantly,

[31] To estimate peer effects in fossil fuel car adoption, I construct separate SSIVs for petrol and diesel vehicles by interacting the three-year lease renewal indicator with individuals' predicted propensities to adopt each fuel type (Section D.3).

[32] One explanation for the longer-lived peer effects among co-workers and neighbors is that individuals may sort into green workplaces or neighborhoods. Restricting the sample to individuals who worked in the same plant or lived in the same neighborhood reveals that the peer effect dynamics persists for constant peer

the peer effect on the uptake of electric cars shows no consistent sign of turning negative. This indicates that interpersonal influences generate additional demand for electric cars and are not merely intertemporal substitution.[33] Aggregating the observed peer effects over two years, I find that one additional electric car in the peer group adds .72 new electric cars in the workplace, .06 in the family, and 2.99 in the neighborhood.[34]

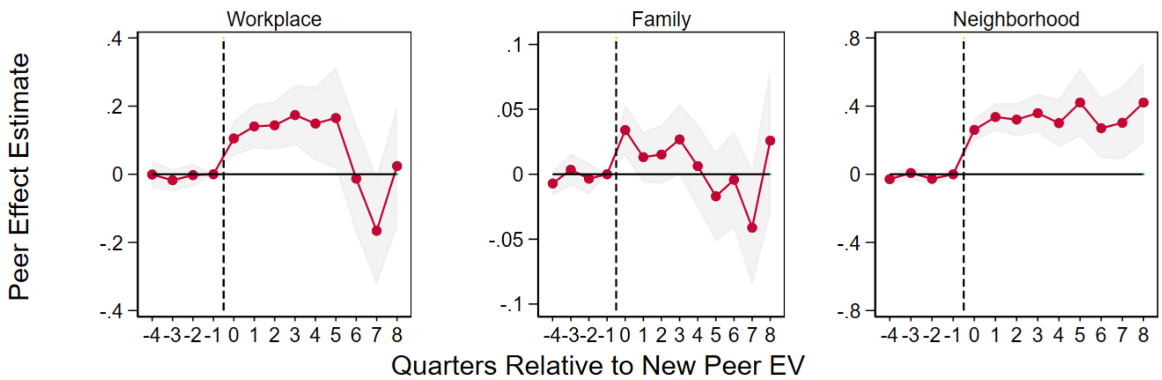

Figure 7: Peer effect dynamics

Notes: The figure displays the peer effect dynamics for new electric cars in the workplace (Panel A), family (Panel B), and neighborhood (Panel C). The dependent variable indicates the number of new electric cars in the peer group up to four quarters prior and up to eight quarters following the initial electric car adoption of peers. The dashed line between period -1 and 0 refers to the new peer electric car adoption period, which resembles the first stage regression in equation (3). The coefficients capture the total peer effect induced by SSIV in quarter q=-1. 95%-confidence intervals reflect robust standard errors, clustered by plants in Panel A, individuals in Panel B, and neighborhoods in Panel C.

D. Environmental impact

The environmental impact of peer effects may extend beyond the electric car decision of peers. A new electric car may also encourage peers to adopt cleaner, non-electric cars, drive less, or shift to alternative modes of transportation (e.g., public transport, cycling). These additional adjustments could reflect raised environmental awareness of commuting choices, shifting social norms, evolving preferences for new technologies, and financial constraints to adopting a new electric car.

While estimating the substitution to other modes of transport remains challenging, I compute how adopting one new peer electric car affects an individual's car-related CO_2

groups (Figure E3), indicating that switching jobs or moving does not explain the different dynamics.

[33]The waiting times for electric cars provide one possible explanation for peer effects over longer periods. Individuals typically select their car before the lease renewal so that the new car's arrival coincides with the lease renewal. If the individual at the leasing renewal exerts peer effects, waiting periods will delay the adoption of new electric cars, and peer effects will appear in subsequent periods.

[34]The peer effect dynamics for all new general cars are considerably shorter (Figure E4), suggesting peer effects are more persistent for new electric cars.

emissions. These are equal to the product of the per-person average vehicle emissions per kilometer ($\overline{V_{i,q}^{CO_2}}$), the per-person average vehicle kilometers traveled ($\overline{KM_{i,q}}$), and the number of cars ($N_{i.q}$).[35] To determine the peer-induced car-related CO_2 emission changes, I differentiate the CO_2 emissions with respect to the peer's electric car adoption for the next six quarters $q = 0, ..., 6$:

$$\triangle CO_{2_{i,q}} = \underbrace{\theta_q^V \cdot \overline{KM_{i,q}} \cdot N_{i.q}}_{\triangle CO_2} + \underbrace{\theta_q^{KM} \cdot \overline{V_{i,q}^{CO_2}} \cdot N_{i.q}}_{\triangle Driving} + \underbrace{\theta_q^N \cdot \overline{V_{i,q}^{CO_2}} \cdot \overline{KM_{i,q}}}_{\triangle Vehicle} \tag{6}$$

The peer coefficients θ_q^V, θ_q^{KM}, and θ_q^N indicate how one new peer electric car influences the vehicle emissions, the kilometers traveled, and the number of cars.[36] Equation (6) implies that the CO_2 emission change ($\triangle CO_{2_{i,q}}$) resulting from the adoption of a new peer electric car is equal to the sum of three effects: changes in (i.) vehicle emissions, (ii.) kilometers traveled, and (iii.) the number of cars. Appendix D.2 describes the derivation of the CO_2 emission model and the regression specifications.

Figure 8 illustrates how one new peer electric car affects the per-person CO_2 emissions in the workplace (Panel A), family (Panel B), and neighborhood (Panel C) by encouraging peers to adopt cleaner cars ("vehicle emission"), drive less ("kilometers traveled"), and reduce the number of owned cars ("number of vehicles") relative to the average CO_2 emission of a person in the peer group. One new peer electric car reduces, in the next quarter, the vehicle emissions of a co-worker's car by .55 grams (with .27 grams resulting from the adoption of new electric cars). To quantify the total effect on car emissions, I multiply the peer coefficient on vehicle emissions by the individuals' kilometers traveled and the number of cars. One new peer electric car causes a .2% CO_2 emission reduction by triggering co-workers to adopt cleaner cars in the next quarter. Around half of the immediate reduction in car emissions is explained by adopting electric cars (red dashed line); the rest is due to non-adopters choosing cleaner fossil fuel cars.[37] Over the next four quarters, the total impact of vehicle emission changes on average CO_2 emissions increased to approximately 1.1% per co-worker.

Furthermore, one new electric car reduces the average kilometers traveled of co-workers by around 154 kilometers and reduces the total number of cars by .02 after one year. This corresponds to a reduction of 2.2% and .8% in CO_2 emissions through changes in driving

[35] I only account for the end-of-pipe emissions of cars, not the emissions throughout production or from charging. Since Sweden's electricity predominantly comes from renewable sources, the carbon intensity of grid electricity is low (Morfeldt et al., 2021), making emissions from charging electric cars negligible.

[36] The CO_2 assessment of peer effects excludes "ripple" effects on the second-hand car market. In Table E7, I find that peer effects have no effect on adopting used electric cars.

[37] To link this to the change in CO_2 emissions solely caused by new electric cars, I multiply the peer effect on electric car adoption (.27 grams) by the emission reduction induced by adopting a new electric car.

behavior and from owning fewer cars, respectively. The empirical evidence that people are driving fewer cars and traveling less frequently by car may indicate a transition to alternative modes of transportation. The total CO_2 emission changes in the workplace caused by peer effects amount to 4.1% after four quarters, which comes from a 1.1% reduction in vehicle emissions, a 2% reduction by driving less, and a 1% reduction in the number of cars. Figure E5 confirms that the peer effect results on the total CO_2 emission align closely with the sum of the CO_2 emission changes through these three margins.

The peer-induced CO_2 emission reduction in the family (and neighborhood) corresponds to 4.6% (1.4%) after four quarters, which can be attributed to a 2.5% (.5%) reduction in vehicle emissions, a 2.1% (.5%) reduction by driving less, and a 0% (.4%) reduction in owning fewer cars. One additional new electric car in the family results in a similar CO_2 emission reduction through new electric cars, cleaner non-electric cars, and driving less after four quarters. However, relatives' influence on vehicle emission reduction fades after four quarters and does not lower the number of cars owned. One new peer electric car in the neighborhood results in a persistent CO_2 emission reduction, although the peer influence of neighbors on car-related CO_2 emissions is weaker compared to co-workers' and relatives'.

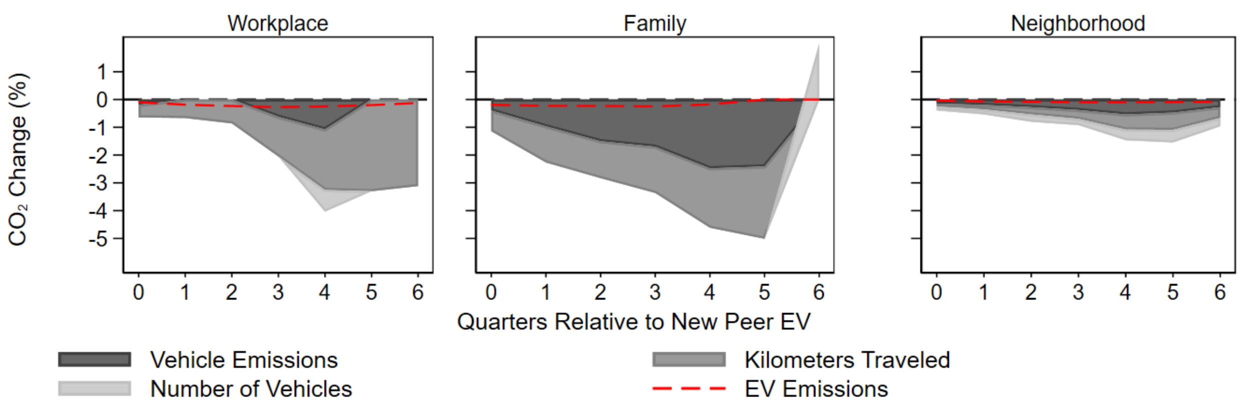

Figure 8: Peer effect on CO_2 emissions

Notes: The figure displays how one additional new electric car impacts the per-person CO_2 emissions through a change in (i.) the average vehicle emissions, (ii.) the vehicle kilometers traveled, and (iii.) the number of owned cars relative to the average CO_2 emission of a person in the workplace (Panel A), family (Panel B), and neighborhood (Panel C). The red dashed line refers to the impact on CO_2 emissions from changes in vehicle emissions of solely electric cars. I set statistically insignificant effects to zero.

The empirical results suggest that peer effects facilitate the transition to a greener transport sector and expand the scope of peer effects by revealing that the total CO_2 emissions of electric cars are significantly greater than the adoption decision of electric cars.[38] While

[38]In addition to the effect on CO_2 emissions, new peer electric cars trigger individuals to adopt cars with greater fuel efficiency and smaller engines (Table E7).

peer effects in electric car adoption result in a persistent CO_2 emission reduction, switching to non-electric cleaner cars, driving less, and reducing the number of owned cars account for most of the CO_2 savings.

E. Mechanisms

Peer effects can influence people's electric car take-up through several mechanisms. Peer effects may serve as a source of information, and individuals are therefore affected through "social learning" about electric cars (Moretti, 2011; Dahl et al., 2014; Herskovic & Ramos, 2020). Although it is difficult to assess what type of information transmission drives the estimated peer effects without data on individual information sets, I empirically test whether the information is transmitted about the leasing contracts, financial incentives, the charging infrastructure, and through exposure or experience with electric cars.

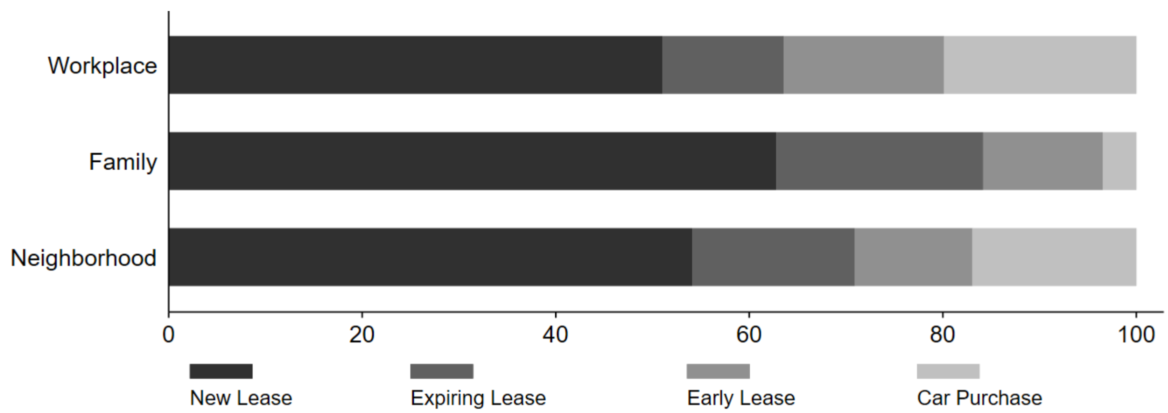

Figure 9: Decomposition of peer effect on leasing

Notes: The figure decomposes the impact of new peer electric car adoptions for different individual leasing contract structures and purchases in workplaces, families, and neighborhoods. The dependent variable for new, expring, and early leases equals the number of new electric cars at a new leasing contract, at the three-year leasing renewal, and renewed before the leasing renewal, respectively. The dependent variables for car purchases refers to purchases of a new electric car. Each bar represents the total treatment effect normalized to 100%. The peer effects on different lease contracts are illustrated in Table E8. I set statistically insignificant, negative effects to zero.

The learning channel may imply that peers share information about how to lease a new car. If leasing information is a key driver of the observed peer effects, I expect peer effects to influence individuals to adopt electric cars with new, expiring or early lease contracts as opposed to individuals with new purchases. Figure 9 demonstrates that peer effects primarily influence the take-up of new leased electric cars, but have a smaller impact on the purchase of new electric cars. To test whether information regarding leasing contracts is specific to electric cars or applies to any new car, I regress whether an individual adopts a new electric car on the number of new fossil fuel cars. Table E9 documents that peer effects are absent for new non-electric cars. This implies that social learning is specific to leasing new electric cars and does not operate through leasing new fossil fuel cars.[39]

A second possible learning mechanism is that peer groups provide information about the financial incentives for adopting a new electric car. Since the penetration of electric cars is still low, there may be a lack of information about the financial incentives of adopting a new electric car. Separating the sample into three distinct subsidy periods — low, medium, and high (Figure B1) —, Figure E6 reveals that the peer effects increase with higher financial incentives for electric cars. As a result, peers are a potential source of information about the financial incentives for electric cars.[40]

A third plausible channel could be learning about charging plug-in electric cars from peers.[41] For public chargers, this may include sharing information about the closest residential charging station, recharge time and cost, and available parking spots with plug-ins. As exposure to charging stations in the residential neighborhood is likely associated with being more informed about the charging infrastructure, I test this hypothesis by breaking up the peer effect estimates from neighborhoods with and without public charging stations. Panel A of Figure E7 shows that peer effects for plug-in electric cars are substantially larger in neighborhoods with public charging stations.

Additionally, living in single-family homes instead of multi-dwelling units may facilitate sharing information about residential charging. Electric car owners in single-family houses may exchange information about home charging station installation, electricity costs, or available government incentives. To test this idea, I estimate the peer effects for hybrid and plug-in electric cars in neighborhoods predominantly consisting of houses or apartments. Panel B of Figure E7 demonstrates that peer effects for plug-in electric cars are exclusively positive in neighborhoods comprised of single-family homes.[42] These results suggest that sharing information about the public and residential charging infrastructure contributes to the observed peer effects.

A peer that has tried a new technology more frequently may be able to provide more

[39] The information channel aligns with the fact that the peer effects are considerably larger in small peer groups, where the transmission of information is straightforward.

[40] An alternative explanation is that individuals are at a different adoption level in higher subsidy periods and the demand elasticities are more responsive to peer's electric car adoption.

[41] The availability of charging station infrastructure at home and at work has been argued to play a crucial role in the EV decision (Springel, 2021; Li, 2016).

[42] The visibility of electric cars may also serve as a mediator for information transmission, such that electric cars in a driveway have stronger visibility and attributability than those parked near apartment buildings. Previous research has argued that one determinant of the relatively high market share of the Toyota Prius was its differentiated design, which made it more recognizable in the neighborhoods (Kahn, 2007; Ozaki & Sevastyanova, 2011).

detailed information about its characteristics. To assess whether the experience with electric cars drives information transmission, I compare the strength of peer effects for electric cars driven more frequently ($> 12,000$ km annually) to those driven less frequently ($< 8,000km$ annually) in Figure E8. Consistent with this experience channel, I find that the estimated peer effects are greater among peers who drive their electric cars more, which suggests that information emerges due to the peer's experience with electric cars. The distinction between low and high usage is most pronounced in neighborhoods where exposure to electric cars is expected to influence peer effects the most.

In addition to the purely informational value, peers' electric car adoption may also directly enter the individual's utility function through a "preference channel" (Mas & Moretti, 2009; DellaVigna et al., 2016; Bursztyn et al., 2018). Peer effects can, for example, serve as an instrument for enforcing norms through social reputation concerns, which directly enter an individual's utility function (Benabou & Tirole, 2011; Jia & Persson, 2021). Social reputation in adopting an electric car can operate through the honor of being an early adopter or the fear of being shamed for driving a gas guzzler. The empirical results in Figure E6, however, indicate that the peer effects are particularly large when there are subsidies for electric cars. As financial incentives reduce the social reputation from adopting an electric car, the financial motives of peer effects dominate the social reputation concerns in the context of electric cars. Moreover, Figure E9 shows that peer effects increase as the electric car ownership in the peer group progresses. This implies that social reputation is unlikely to be the primary driver as social reputation associated with early adoption should diminish as more peers own electric cars, potentially leading to declining peer effects.

Assuming that social norms operate through conforming to the average car type of peers in the utility function (Akerlof, 1997; Kandel & Lazear, 1992; Bernheim, 1994), deviating from the average CO_2 vehicle emissions of peers becomes more costly in a conformity model. Hence, I split the sample into peer groups with low- and high-emitting vehicle fleets in Figure E10. The peer effects in low-emitting fleets are substantially larger in neighborhoods, indicating that conformity to social norms is mainly present among neighbors.

V. Optimal policy

Policymakers frequently offer subsidies to encourage the adoption of durable goods, such as EVs, to achieve environmental goals. Because adopting electric cars influences peers' vehicle choice and the associated externalities, designing an optimal subsidy that accounts for these peer effects remains an open research question. To characterize the optimal Pigouvian subsidy that internalizes peer interactions, I combine a discrete choice model over the vehicle type with the effect of peer influences.

A. Model of vehicle choice

Consider a discrete choice model in which consumers choose between a new fossil fuel and an electric car.[43] Consumers obtain utility from vehicle kilometers traveled over the life of the selected car, either fossil fuel kilometers KM^f or electric kilometers KM^e, and a composite consumption good x (with price normalized to one). Fuel and car prices are fixed. The indirect utility of purchasing a new fossil fuel car is

$$W^f \;=\; \max_{x,KM^f} x \;+\; f(KM^f) \;\; such\ that \;\; x + p^f_{KM} KM^f \;=\; I - p^f, \tag{7}$$

where p^f is the price of the fossil fuel car, p^f_{KM} is the price of a fossil fuel kilometer, I is income, and f is a concave function. Similarly, the indirect utility of purchasing a new electric car is

$$W^e \;=\; \max_{x,KM^e} x \;+\; h(KM^e) \;\; such\ that \;\; x + p^e_{KM} KM^e \;=\; I - (p^e - \tau), \tag{8}$$

where p^e is the price of the electric car, p^e_{KM} is the price of an electric kilometer, and h is a concave function. The government provides a subsidy τ for purchasing a new electric car. Differences in the functions f and h capture any difference in attributes between fossil fuel and electric cars.

Consumers generate emission damages by driving but disregard these externalities when choosing the type of car. Accordingly, I define Φ^f and Φ^e as the sum of unincorporated marginal externalities (in \$) over the driving lifetime of a fossil fuel and electric car, respectively. In addition, consumers disregard how adopting electric cars impacts the externalities of their peers, whom they influence to acquire an electric or fossil fuel car. The lifetime damages from the peer electric car adoption correspond to the externalities of the peer-induced fossil fuel ($\Phi^f \theta^f$) and electric car ($\Phi^e \theta^e$).

B. Deriving peer effects subsidies

The policymaker selects a subsidy for electric cars that maximizes the welfare associated with the purchase of a new car. The welfare is defined as the sum of expected utility from a new car purchase, and the expected government expenditures R minus the expected externalities from the fossil fuel and electric car adoption, including their impact on the externalities from the peers' electric car adoption:

[43] Theoretical discrete choice models in the transportation literature include De Borger (2001), De Borger and Mayeres (2007), and Holland et al. (2016).

$$\mathcal{W} \;=\; \mu(ln(exp(\frac{W^e}{\mu}) \;+\; exp(\frac{W^f)}{\mu})) \;+\; R \;-\; (\pi\Phi^f + (1-\pi)(\Phi^e(1+\theta^e) + \Phi^f\theta^f)). \quad (9)$$

π and $(1-\pi)$ correspond to the probabilities of adopting a fossil fuel and electric car. Because the first-best policy is differentiated Pigouvian taxes on both types of kilometers, I refer to the welfare-maximizing subsidies as second-best. Optimizing the welfare function gives the following proposition (see Appendix F for all proofs):

Proposition 1. *The second-best subsidy for electric cars that internalizes how peer effects in electric car adoption influence the subsequent adoption of electric and fossil fuel cars is given by*

$$\tau^* \;=\; \Phi^f - \Phi^e - \theta^f\Phi^f - \theta^e\Phi^e.$$

In the absence of peer effects ($\theta^f = \theta^e = 0$), the second-best subsidy for electric cars τ equals the discrepancy between the sum of all unincorporated externalities over the lifespan of a fossil fuel and electric car (Holland et al., 2016; Rapson & Muehlegger, 2023). I refer to this difference, $\Phi^f - \Phi^e$, as the marginal external benefit of an electric car. When the policymaker incorporates the influence of peer effects, Proposition 1 documents that the second-best purchase subsidy for electric cars equates to the marginal benefits of an electric car minus the peer-induced externality changes of fossil fuel and electric cars, which correspond to the peer effect on adopting fossil fuel and electric cars multiplied by their respective externalities. In Appendix F.2, I extend the framework to allow fossil fuel cars to generate peer effects on subsequent electric and fossil fuel car adoptions.

Positive peer effects in the adoption of fossil fuel and electric cars ($\theta^f, \theta^e > 0$) both diminish the subsidy as the additional fossil fuel and electric cars among peers exacerbate the externalities (assuming strictly positive externalities). If peer effects of electric cars lead to additional fossil fuel and electric cars, the second-best subsidy, factoring in peer effects, is lower than the marginal benefits from electric cars. However, a peer electric car adoption that is caused by a substitution from fossil fuel cars ($\theta^f < 0$) increases the second-best subsidy by the magnitude of avoided externalities from fossil fuel car adoption.

Hence, the impact of peer effects on the second-best subsidy depends on how much electric cars displace fossil fuel cars. To illustrate this, I present the following three cases:

1. *Partial displacement* ($|-\theta^f| < \theta^e$): If peer effects for electric cars partly displace the fossil fuel car adoption, the sign of the subsidy is ambiguous because the reduction in externalities associated with fossil fuel car adoption may not outweigh the additional externalities arising from the increased adoption of electric cars by peers.

2. *One-to-one displacement* ($-\theta^f = \theta^e = \theta$): If the adoption of electric cars is accompanied by a corresponding reduction in fossil fuel cars, the subsidy scales proportionally to the peer-induced marginal external benefits of electric cars, $\theta(\Phi^f - \Phi^e)$.

3. *Excess displacement* ($|-\theta^f| > \theta^e$): If peer effects lead to a greater reduction in fossil fuel cars than the corresponding increase in electric cars (e.g., substitution to other transport modes), then the subsidy exceeds the peer-induced marginal external benefits of adopting electric cars.

C. Computing peer effects subsidies

To implement the peer effects subsidy for electric cars, I start by calculating the lifetime CO_2 emission damages from adopting a new fossil fuel and electric car. The lifetime CO_2 emission damages for fossil fuel and electric cars correspond to the product of average vehicle emissions, the annual vehicle kilometers traveled, and the average lifespan. Next, I multiply the CO_2 emission damages by the current Swedish carbon tax rate of \$126 per ton of CO_2, which approximates the social cost of carbon. The unincorporated lifetime CO_2 emission damages are estimated at $\$3,370$ for fossil fuel cars and $\$1,130$ for electric cars in the Swedish fleet. Without accounting for peer effects, the second-best subsidy for electric cars is $\$2,240$ in Sweden (column 1, Table 2).[44]

To compute the peer-induced CO_2 emission changes, I combine the CO_2 emission damages with the estimated peer effects on the adoption of fossil fuel θ^f and electric cars θ^e for each peer group (Figure 6). The peer-induced externality changes from the individual's electric car adoption imply that peer effects reduce emission damages by \$1,482 and suggest that electric cars may lead to greater emission reductions than expected (columns 2-4, Table 2). Hence, the optimal peer effects subsidy for electric cars should be \$3,722 or 66.2% higher compared to a Pigouvian subsidy without peer effects (columns 5, Table 2). Put differently, if adopting an electric car reduces total CO_2 emissions by 17.8 tons (i.e., the average lifetime emissions difference between a new electric and fossil fuel car), the combined emissions reductions from all of the individual's peers would amount to 11.8 tons.

As peer effects lead to a greater displacement of fossil fuel cars than the corresponding increase in electric cars within workplaces and families, the effect on the optimal peer effects subsidy exceeds the magnitude of the peer effect estimate in both peer groups. This is because peer effects mitigate externalities not only by displacing fossil fuel with electric cars

[44] The range of estimates is close to the second-best subsidy for electric cars of $\$2,785$ in California (Holland et al., 2016). Applying the social cost of carbon of \$241 per ton, as reported by the Environmental Protection Agency (2022), the estimated second-best subsidy for electric cars in Sweden also aligns with the difference of driving CO_2 externalities from gasoline and electric vehicles (\$6,561) in Allcott et al. (2024).

but also by reducing fossil fuel cars beyond the individual electric car adoption. Specifically, peer effects lowered emission damages by $767 among co-workers and $202 among relatives (corresponding to reductions of 34.3% and 8.9% relative to a Pigouvian subsidy). Among neighbors, peer effects lead to a one-to-one displacement from fossil fuel to electric cars. This implies that the optimal peer effects subsidy increases by 22.9%, which is proportional to the magnitude of peer effects associated with electric car adoption in neighborhoods.

Table 2: Peer effects subsidy

Pigou Subsidy	Peer Externalities $(-\theta^f \Phi^f - \theta^e \Phi^e)$			Optimal Peer Subsidy
$(\Phi^f - \Phi^e)$	A. Workplace	B. Family	C. Neighborhood	
2,240	767.4 (34.3%)	201.6 (8.9%)	513.4 (22.9%)	3,722 (66.2%)

Notes: This table presents the components of the optimal peer effects subsidy. Column 1 reports the optimal Pigouvian subsidy for electric cars. Columns 2 to 4 detail the peer-induced externality changes associated with fossil fuel and electric cars for each peer group. The %-effects relative to the Pigouvian subsidy are reported below. Column 5 provides the optimal peer-effects subsidy as derived from Proposition 1. All subsidies and externalities are expressed in real 2021$.

Incorporating peer effects of fossil fuel cars increases the second-best subsidy for electric cars by the peer-induced emissions of the additional fossil and electric cars (Proposition 2). If peer effects in fossil fuel cars spur the subsequent adoption of fossil fuel cars, the subsidy for electric cars should rise to reflect the added emissions. More generally, strong peer effects for an existing brown technology that reduce demand for a new green technology suggest the need for a higher subsidy. However, since peer effects for fossil fuel cars only have a minor impact on subsequent fossil fuel adoption (Table E9), the optimal peer effects subsidy remains unaffected.

Allowing peer effects to influence the indirect utility of purchasing a new electric car modifies the optimal subsidy depending on the underlying mechanism ($\frac{\delta W^e}{\delta \theta^e} \lesseqgtr 0$). While information transmission suggests to increase subsidies for electric cars, social reputation effects justify lower subsidies.[45]

[45] If the information provided by peers reduces the uncertainty about the characteristics or the usage of electric cars, this increases the indirect utility of adopting a new electric car (Moretti, 2011; Dahl et al., 2014). As electric car adopters in peer groups diffuse information, the optimal subsidy compensates for the additional utility that future adopters derive from the information. In contrast, if a peer's electric car adoption affects individuals' indirect utility through social reputation (Benabou & Tirole, 2006, 2011), the optimal subsidy should reflect its potential to diminish the social prestige associated with electric cars.

VI. Concluding remarks

The transition to EVs is a cornerstone of global decarbonization strategies, with governments worldwide implementing various subsidy schemes to stimulate EV adoption. However, the effectiveness of these policies are shaped not only by direct financial incentives but also by peer effects, which can amplify the transition to cleaner transportation.

This paper provides evidence of peer effects in electric car adoption within workplaces, families, and neighborhoods. On average, one new electric car causes, in the next quarter, an additional .094 new electric car acquisitions in the workplace, .023 in the family, and .22 in the neighborhood. The peer-driven adoption of electric cars displaces the demand for fossil fuel cars and reflects incremental demand for electric cars rather than intertemporal substitution of future planned purchases. Furthermore, peer effects result in a transition towards more environmentally-friendly forms of transportation by encouraging individuals to adopt cleaner non-electric cars, drive less, and reduce the number of cars.

Finally, the paper outlines an optimal environmental subsidy that incorporates these peer effects. The conceptual framework highlights that the impact of peer effects on the optimal subsidy depends on the degree to which peer-induced electric car adoption displaces fossil fuel cars. When accounting for the peer-induced emission reductions, the findings suggest that the optimal subsidy should exceed the traditional Pigouvian level by 66.2%. In addition, information campaigns about leasing electric cars may be an effective complementary policy, as the empirical findings align with an information transmission mechanism about financial incentives, leasing contracts, charger infrastructure, and exposure to electric cars.

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Online Appendix

Peer Effects in Electric Car Adoption:
Evidence from Sweden

Sebastian Tebbe

A. Additional summary statistics

Table A1: Descriptive statistics

	Mean	Std. dev.	Min	Max	Obs.
A.Socio-Demographic Data					
Age	47.46	18.27	18	117	73,639,741
Female	0.50	0.50	0	1	73,639,741
Annual Gross Salary (in tho.)	332.67	277.27	0	130,376	51,285,915
Annual Unemployment Days	5.92	34.89	0	366	73,639,741
Self-Employed	0.07	0.26	0	1	73,639,741
Retired	0.20	0.40	0	1	73,639,741
Married or Cohabitant	0.56	0.50	0	1	73,639,741
At Least 1 Child	0.44	0.50	0	1	73,639,741
Years of Education	12.14	2.62	7	20	72,133,961
At least 1 Car	0.41	0.49	0	1	73,639,741
Number of Cars	0.49	0.67	0	3	73,639,741
B.Vehicle Data					
Vehicle Kilometers Traveled	11904.59	7641.26	0	497,937	36,197,561
Leased Vehicles (%)	0.02	0.15	0	1	36,197,561
Vehicle Age	10.79	8.75	0	117	36,197,534
Vehicle Weight (kg)	1475.34	266.33	0	17,910	36,197,561
Engine Power (kW)	102.79	38.54	0	1,777	36,197,561
Vehicle Fuel Efficiency (l/100km)	5.95	3.04	0	66	36,197,561
Vehicle Emissions (g CO2/km)	122.31	84.07	0	500	36,197,561
C.Charging Infrastructure Data					
Number of Charging Stations	0.36	1.55	0	67	2,104,711
Charging Station Installation	0.04	0.19	0	1	2,104,711
Number of Plug-ins	1.70	17.65	0	1,519	2,104,711
Power Wattage (kWh)	19.13	22.11	0	350	232,448

Notes: Panel A presents individual socio-demographic statistics on the individual-by-year level from 2012 to 2021. Panel B presents descriptive statistics on the Swedish vehicle registry data, which are at the vehicle-by-year level. Panel C presents descriptive statistics for the charging infrastructure based on the residential location of individuals at the neighborhood-by-year level between 2012 and 2021. All incomes, revenues, and costs are expressed in 2021 Swedish kronor.

Table A2: Summary statistics for the population and EV owners

	Population		Vehicle Owner		
	Mean	Std. Dev.	Car Owner	Alt. Fuel	Electric
A.Socio Demographic Variables					
Age	49.17	18.57	52.70	52.03	51.44
Female	0.50	0.50	0.39	0.36	0.33
Gross Salary (in tho.)	346.25	294.55	394.49	379.68	493.06
Disposable Income (in tho.)	312.88	1800.71	336.57	306.72	448.44
Annual Unemployment Days	11.35	48.57	8.15	8.87	6.54
Self-Employed	0.07	0.26	0.05	0.04	0.06
Married or Cohabitant	0.55	0.50	0.63	0.66	0.76
At Least 1 Child	0.43	0.49	0.34	0.34	0.34
Years of Education	12.28	2.62	12.40	12.55	13.28
Share Commute	0.66	0.48	0.71	0.73	0.78
Distance Commute	39.56	110.50	37.60	36.16	39.52
B.Charging Network					
Number of Charging Stations	3.57	6.25	2.78	2.63	2.84
Charging Station Installations	0.20	0.40	0.17	0.16	0.17
Number of Plug-ins	25.62	86.35	16.39	15.04	19.36
Power Wattage (kWh)	11.36	18.21	10.44	10.42	9.81
Number of Observation	7,764,482		3,243,900	179,944	188,371

Notes: This table reports descriptive statistics on socio-demographic variables (Panel A) and the public charging network (Panel B) for the Swedish working-age population (18 or older) and for three fuel types of car owners: all car owners, alternative fuel car owners, and electric car owners in 2021.

Table A3: Peer group statistics

	Mean	Std. dev.	Min	Max	Obs.
A.Workplace Network					
Number of Co-workers	45.37	37.57	5	150	109,259,323
New Car Registrations	7.33	8.61	0	198	109,259,323
New EV Registrations	0.75	1.47	0	70	109,259,323
Number of Lease Renewals	0.72	1.33	0	20	109,259,323
B.Family Network					
Number of Relatives	7.34	6.44	1	182	263,032,710
New Car Registrations	0.90	1.51	0	37	263,032,710
New EV Registrations	0.09	0.35	0	12	263,032,710
Number of Lease Renewals	0.10	0.37	0	9	263,032,710
C.Neighborhod Network					
Number of Neighbors	261.41	326.20	5	2,794	274,318,310
New Car Registrations	30.48	33.57	0	335	274,318,310
New EV Registrations	2.82	3.86	0	39	274,318,310
Number of Lease Renewals	3.14	4.31	0	44	274,318,310

Notes: The table presents summary statistics for workplaces (Panel A), families (Panel B), and neighborhoods (Panel C) summed over all periods.

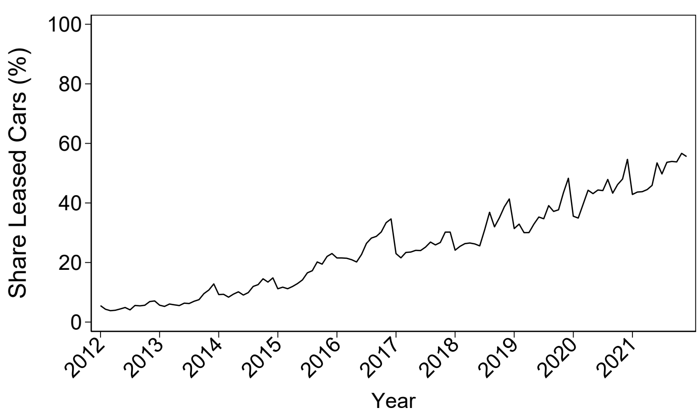

Figure A1: Share of leased cars

Notes: This figure displays the monthly share of all newly leased cars relative to the total number of new registrations by individuals in the Swedish vehicle market between 2012 and 2021.

B. Swedish vehicle reforms

B.1. Vehicle subsidies

Between 2012 and 2021, subsidies for "green" vehicles were implemented through three distinct policies: the super green car premium ("*supermiljöbilspremie*"), which was in effect from January 2012 to June 2018, and two phases of the climate bonus ("*klimatbonus*") as part of the bonus-malus system. The first phase of the climate bonus spanned from July 2018 to December 2019, while the second phase was active from January 2020 to December 2021.[46] The Swedish government declared its primary purpose to increase sales and use of new cars with low climate impact, to contribute to lower CO_2 emissions, and to a fossil-independent vehicle fleet. The financial incentives of the vehicle subsidies with respect to the CO_2 emission level is shown in Figure B1.

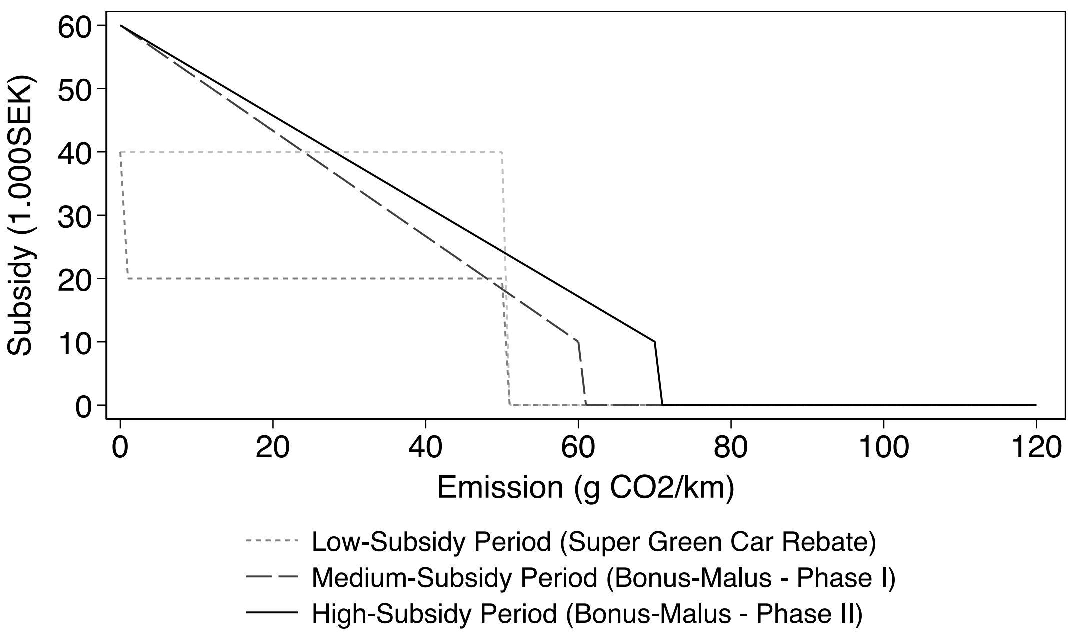

Figure B1: Swedish vehicle subsidies

Low-subsidy period. In September 2011, the Swedish Government approved the "Super Green Car Rebate" with a budget of 200 million SEK, which effectively started in January 2012 (Ministry of the Environment, 2011). Irrespective of the fuel type, the rebate was provided to those vehicles with emission levels below $50g/km$ of CO_2. Between 2012 and 2015, individuals received a subsidy of 40,000 SEK for new vehicles fulfilling the emission

[46] Before my study period, the green car rebate program ("*miljöbilspremie*"), active from April 2007 to June 2009, consisted of a $10,000$ SEK transfer to all private individuals six months after buying a vehicle that is classified as "green."

threshold. Between 2016 and June 2018, the maximum rebate of cars with zero CO_2 emissions remained at 40,000 SEK, while the purchase of new cars with emission levels between 1-50g/km was rewarded with 20,000 SEK.

Medium-subsidy period. The Swedish Government issued an ordinance in December 2017 about a climate bonus rebate as part of the new bonus-malus system. The amendment was applied in July 2018 and only affects new vehicles registered in the Road Traffic Register as of that date (Ministry of the Environment, 2017). The climate bonus applies to vehicles that emit a maximum of 60 g/km of CO_2. For purely electric cars and hydrogen cars with zero emissions, the highest possible bonus amounts to 60,000 SEK. The bonus is reduced by 833 SEK for every gram of CO_2 emitted per kilometer.

High-subsidy period. From January 2020 onward, the CO_2 limit for new registrations to receive a climate bonus has been increased to 70 g/km and the reduction per additional CO_2 emission was replaced by 714 SEK. This change resulted in higher subsidies for plug-in electric vehicles and included a broader range of plug-in models, as more vehicles could qualify under the increased CO_2 limit. The bonus can not exceed 25% of the price charged for the new car when the model was first introduced on the Swedish market.

B.2. Private use of a company car

Employers may provide a car fringe benefit if they make available a car they own or lease to an employee for their private use. Vehicles used exclusively for work-related purposes do not incur fringe benefits taxation in Sweden if used for private purposes less than 1000 kilometers and fewer than ten times annually. The fringe benefit value equals 9% of the new car price (p), a certain percentage of the price base value (PBV), and 75% of the government bond interest rate (GB) multiplied by the new car price:

$$FBV = p \cdot \ .09 \ + \ PBV \ + \ .75 \cdot \ GB \cdot \ p, \tag{B1}$$

if the new car price was less than 7.5 times the price base value. Table B1 shows the price base value, its percentage, and the government bond interest rate required to calculate the fringe benefit value for each year. The fringe benefit value is added to the employee's gross total income, and tax is paid accordingly.

After 2016, or if the price was higher than 7.5 times the price base value, the fringe benefit value increased by 20% of the price over 7.5 times the price base value, which increases the value for more expensive cars:

$$FBV = p \cdot \ .09 \ + \ PBV \ + \ .75 \cdot \ GB \cdot \ p \ + .2 \cdot \ (p - 7.5 \cdot \ PBV). \tag{B2}$$

This approach, however, would favor petrol and diesel over electric cars, given their comparatively lower purchase price. Since the Swedish Government's decision in 1999 regarding preferential taxation of green benefit cars (Ministry of Finance, 1999) and the decision on the reduction in the benefit value for certain green cars in 2001 (Ministry of Finance, 2001), the taxable value for the private use of company cars is reduced in two steps if the vehicle runs on alternative fuels and therefore reduces the amount of income taxes that need to be paid on it. First, the benefit value of the alternative fuel is reduced to the benefit value of a comparable petrol or diesel car. Second, an additional reduction of 20% to 40% with a maximum of 8,000 to 16,000 SEK can apply depending on the fuel type and vintage year.

- For battery electric cars, plug-in hybrids and cars driven by gas (not LPG) there is a reduction of the value for personal income taxation of 40% with a maximum of 16,000 SEK compared to the taxation value of the corresponding or comparable car driven by petrol or diesel. From 2017, the maximum reduction was decreased to 10,000 SEK.
- For cars driven by LPG, rapeseed oil, or other environmentally adjusted fuels, the benefit value is the same as for the corresponding petrol or diesel car

If the employer pays for all the fuel, the employee must treat 120% of the value of the fuel used for private driving as personal income.

Table B1: Fringe benefit values for green cars

Year	Price Base Value (SEK)	% of Price Base Value	Government Bond Interest Rate (%)
2012	40,000	31.7	1.65
2013	44,500	31.7	1.49
2014	44,000	31.7	2.09
2015	44,500	31.7	0.90
2016	44,300	31.7	0.65
2017	44,800	31.7	0.50
2018	45,500	29	0.50
2019	46,500	29	0.51
2020	47,300	29	0.50
2021	48,300	29	0.50

C. Shift-share instrument

C.1. Neural network design

The neural network model in equation (2) used to estimate the propensity of acquiring a new electric car at the leasing renewal is trained using a stratified training and testing split. I train the model with 75 % of the quarterly data and use it to predict propensities for 25% of the test data.[47] The neural network is trained using a stochastic gradient descent algorithm with momentum and an exponential decaying learning rate. The underlying learning rate parameter is initially set to $\eta = .01$, and the learning rate decreases exponentially. When the weights are updated, I include an exponentially weighted average of the previous updates. The model learns to approximate the function using 50 training epochs and a batch size of 250. The neural network consists of two hidden layers with layer sizes of 25 and 15. Batch normalization is used between the hidden layers to re-parametrize the model and standardize units. The classification metric to train the model is the mean squared error. The model uses the complete set of control variables.

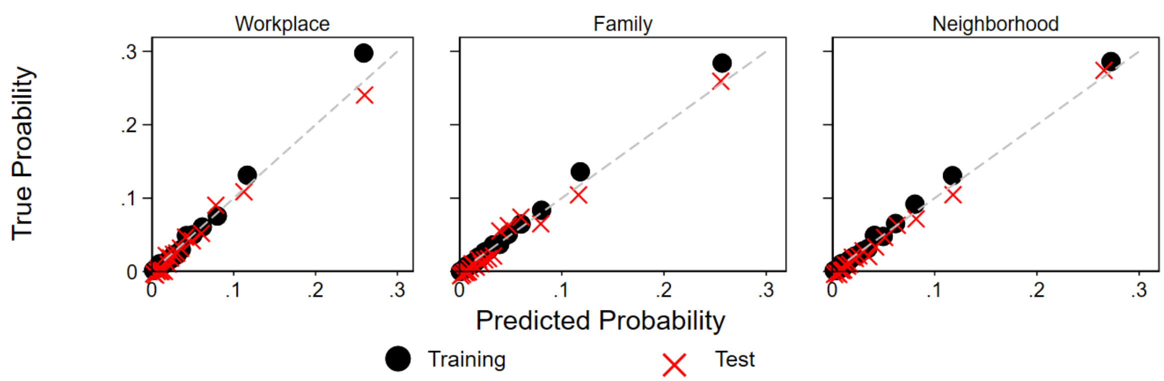

Figure C1: Propensity score predictions

Notes: The figures display binscatter plots of the predicted against the realized probability to acquire a new electric car conditional on being at the three-year leasing renewal cutoff for the training data set (black dot) and the test data set (red cross) in the workplace (Panel A), family (Panel B), and neighborhood (Panel C). The y-axis plots the actual probability of electric car adoption within 5-percentile bins of predicted peer electric car adoption. All panels are restricted to individuals at the three-year leasing contract renewal between 2012 and 2021.

Subsequently, I evaluate how the estimated propensities relate to the realized propensities of electric cars. Figure C1 displays the binscatter plots of the predicted against the realized probability of acquiring an electric car at the three-year renewal cutoff for both

[47]It is crucial to test on a held-out data set as training using in-sample data would run the risk of overfitting the neural network model, which would bias the coefficients of the SSIV towards the OLS coefficients.

the hold-out test set ("Test") and the actual training data set ("Training") in the workplace (Panel A), family (Panel B), and neighborhood (Panel C). The predicted adoption of electric cars in the training and test data closely aligns with the 45-degree line, which suggests that the neural network prediction accurately reflects electric car take-up decisions at the renewal cutoff. The 5%-binned predicted probabilities to lease a new electric car at the renewal timing range between 0% and 40%. This highlights the high degree in individual electric car adoption that is exploited in the SSIV-design.

Another metric used in machine learning to assess the performance of a predictive model at various thresholds is the ROC-AUC curve. The Receiver Operator Characteristic (ROC) curve is a probability curve that plots the true positive rate (y-axis) against the false positive rate (x-axis) at various thresholds. The Area Under the Curve (AUC) score equals the area under the curve of the formed line and is the measure of a classifier to distinguish between classes. Intuitively, it corresponds to the probability that a classifier will rank a random positive example above a random negative one. When the AUC equals one, the classifier can perfectly distinguish between classes, while .5 reflects a meaningless model that is as good as random. Figure C2 shows the ROC curves for both the hold-out test set and the actual training data set in the workplace (Panel A), family (Panel B), and neighborhood (Panel C).

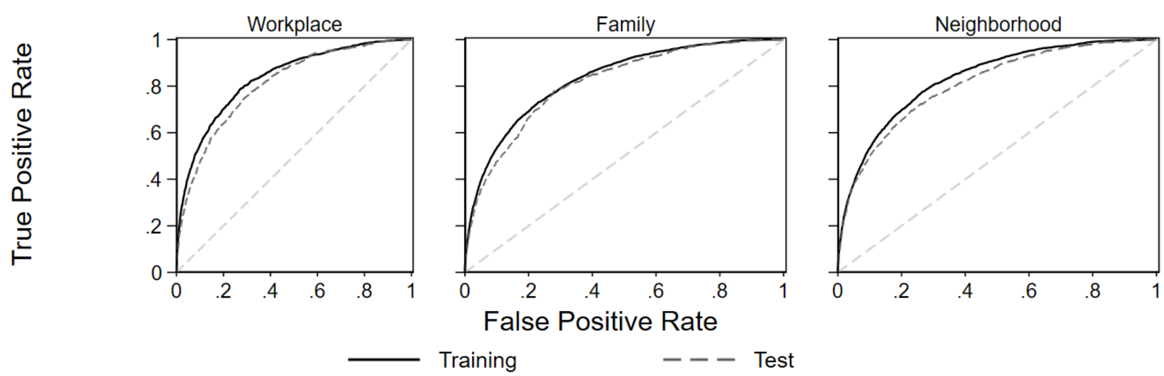

Figure C2: ROC-AUC curves

Notes: The figures present Receiver Operating Characteristic (ROC) curves for the estimated probabilities of adopting a new electric car at the contract renewal in the workplace (Panel A), family (Panel B), and neighborhood (Panel C). The training set is indicated in solid lines, and the test set in dotted lines. All Panels include individuals at the three-year leasing renewal threshold between 2012 and 2021.

C.2. Validity checks

Table C1 reports summary statistics for the contract renewal shocks computed with predicted propensities across workplaces, families, and neighborhoods. To justify the assumption that there are many conditionally uncorrelated shocks, I document that the average shock exposure converges to zero, which can be interpreted as exploiting a large effective sample size. The effective sample size, measured as the inverse of the Herfindahl index (HHI) $(1/\sum_{j,q} Pr(V^e)^2_{j,q})$, is high: 358,077 across peer group-by-quarter, and the largest shock weight is below .00001% across peer group-by-quarter. The distribution of shocks also indicates a sufficient dispersion with a standard deviation of .0196 and an interquartile range of .0017. This implies a sizable degree of variation at the peer group level, and a few particular peer groups do not drive the results. As a large number of shocks is key for the validity of the empirical strategy, the last row indicates that the leasing contract renewal leverages 27,619, 80,817, and 50,409 shocks to the car adoption in the workplace, family, and neighborhood.

Table C1: Shock summary statistics

	Peer Groups		
	A.Workplace	B.Family	C.Neighborhood
Mean	0	0	0
Standard Deviation	.0196	.0142	.4438
Interquartile range	.0017	.0006	.3269
Effective sample size (1/HHI)			
Across peer groups and quarters	358,077	85,416	31,777,512
Largest weights			
Across peer groups and quarters	<.0001	<.0001	<.0001
Observation counts			
N(peer group shocks)	27,619	80,817	50,409
N(peer groups)	252,352	7,314,474	4,696

Notes: This table summarizes the distribution of contract renewal timings across workplaces (column 1), families (column 2), and neighborhoods (column 3). Shocks are measured as the total number of peers at the three-year leasing contract renewal. Shares are computed as the propensity of adopting a new electric car using a neural network, as described in equation (2). All statistics are weighted by the average exposure shares.

C.3. Computation of standard errors

To understand how severe the dependencies are in the error term, I follow Eckles et al. (2016), Zacchia (2020), and Bailey et al. (2022) to explore the robustness of my statistical inference to various approaches of constructing standard errors.[48] Specifically, I compare the heteroskedasticity-robust standard error to individual, workplace, organization, neighborhood, and the demographic statistical area ($DeSO$) clustered standard errors in workplaces, families, and neighborhoods.

Figure C3 documents that individual-clustered standard errors are similar in size to heteroskedasticity-robust standard errors across all peer groups, implying no correlation across individuals. Standard errors increase by 6.4% in the workplace and 18.4% in the neighborhood if clustered on the peer-group level, suggesting that standard errors may be correlated across individuals similarly exposed to the same set of shocks. However, standard errors are unaffected when moving to the organization- and DeSO-level, indicating that residual dependencies do not influence standard errors in larger groups. Hence, I cluster standard errors at respective peer-group level in the non-overlapping workplace and neighborhood. In the overlapping family peer group, I cluster the standard errors on the individual-level to account for the most possible across-individual dependencies in the error term.

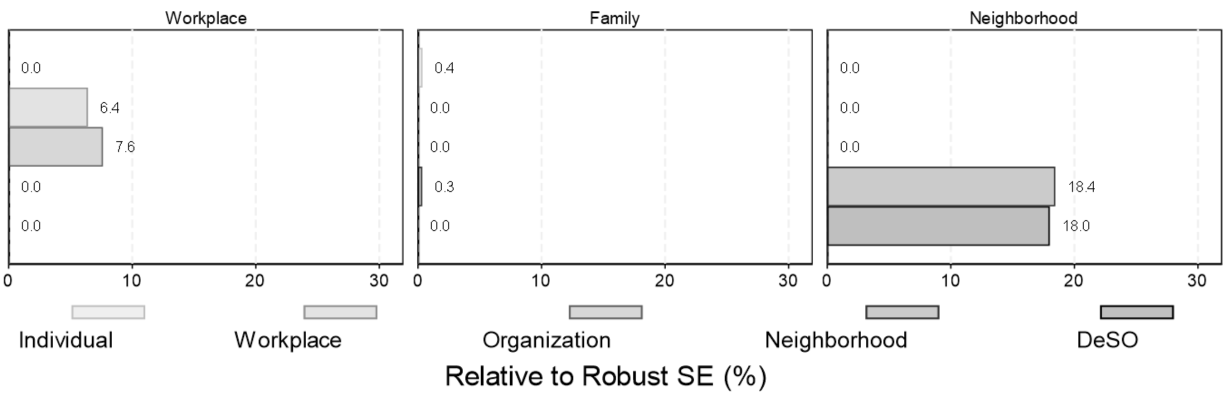

Figure C3: Comparison of standard errors

Notes: The figure compares standard errors using various clustering approaches to heteroskedasticity-robust standard errors for the shift-share IV in workplaces (Panel A), families (Panel B), and neighborhoods (Panel C). The standard errors are clustered at the individual-level (top row), the neighborhood-level (second row), the DeSO area (third row), the workplace (fourth row) and the organization (fifth row).

[48]Eckles et al. (2016) and Zacchia (2020) propose to partition the social graph into groups with limited cross-community dependence, and to cluster the standard errors at the community level.

D. Regression specifications

D.1. Peer effect dynamics

To estimate the dynamics of peer effects, I expand the horizon over which peer effects are measured to capture the exact timing of the peer effects. The dependent variable equals the individual electric car take-up four quarters prior and up to eight quarters following the initial peer electric car adoption: $V^e_{i,\tau}$ for $\tau = -4, ..., 8$. By defining the expiring leasing contract in $q = -1$ as the reference quarter, the dynamic reduced form equation can be written as:

$$V^e_{i,q+\tau} \;=\; \alpha + \theta^e_\tau \sum_{j\epsilon N_i} V^{3y}_{j,q-1} \cdot \widehat{Pr}(V^e \mid V^{3y}_{j,q-1} = 1) + \gamma \overline{X}_{p-i,q} + \delta X_{i,q} + \phi_q + \varepsilon_{i,q} \qquad \tau \in \{-4, ..., 8\}, \tag{D1}$$

where θ^e_τ captures the dynamic peer effects four quarters prior and eight quarters following the peer electric car adoption. θ^e_τ accounts for peer effects' direct and indirect social forces and how they unfold over time. The first stage equation (3) remains unchanged as the exogenous variation comes solely from the contract renewal in $q = -1$. The underlying model assumes sequential ordering, which implies that individuals who adopt a new electric car subsequently affect peers who acquire new electric cars, but not vice versa.

D.2. Carbon emission model

A person's total car-related CO_2 emissions in a given quarter ($CO_{2,i,q}$) is equal to the vehicle emissions ($V^{CO_2}_j$) multiplied by the vehicle kilometers traveled (KM_j), summed over all cars j n quarter q:

$$CO_{2,i,q} \;=\; \sum_{j\epsilon J} V^{CO_2}_{i,q,j} \cdot KM_{i,q,j} \tag{D2}$$

This can be expressed as the product of the kilometer-weighted average CO_2 emission of cars ($\overline{V^{CO_2}_{i,q}}$), the average kilometer traveled ($\overline{KM_{i,q}}$), and the number of cars ($N_{i.q}$) according to:

$$CO_{2,i,q} \;=\; \overline{KM_{i,q}} \cdot \overline{V^{CO_2}_{i,q}} \cdot N_{i.q} \tag{D3}$$

To measure how peer effects in adopting new electric cars influence a person's car-related CO_2 emission, I differentiate the car-related CO_2 emission of each person in equation (D3) with respect to the peer electric car adoption ($V^e_{p_{-i},q-1}$) in the following equation (D4):

$$\underbrace{\frac{\partial CO_{2,i,q}}{\partial V^e_{p_{-i},q-1}}}_{\triangle CO_{2,i,q}} = \underbrace{\frac{\partial \overline{KM_{i,q}}}{\partial V^e_{p_{-i},q-1}}}_{\theta^{KM}} \cdot \overline{V^{CO_2}_{i,q}} \cdot N_{i.q} + \underbrace{\frac{\partial \overline{V^{CO_2}_{i,q}}}{\partial V^e_{p_{-i},q-1}}}_{\theta^{V}} \cdot \overline{KM_{i,q}} \cdot N_{i.q} + \underbrace{\frac{\partial \overline{KM_{i,q}}}{\partial V^e_{p_{-i},q-1}}}_{\theta^{N}} \cdot \overline{KM_{i,q}} \cdot \overline{V^{CO_2}_{i,q}} \tag{D4}$$

I can rewrite the impact of peer effects on CO_2 emissions as:

$$\triangle CO_{2,i,q} = \underbrace{\theta^e_N \cdot \overline{V^{CO_2}_{i,q}} \cdot \overline{KM_{i,q}}}_{\triangle Cars} + \underbrace{\theta^e_{KM} \cdot \overline{V^{CO_2}_{i,q}} \cdot N_{i.q}}_{\triangle Driving} + \underbrace{\theta^e_V \cdot \overline{KM_{i,q}} \cdot N_{i.q}}_{\triangle CO_2} \tag{D5}$$

Equation (D5) implies that the change in CO_2 emissions resulting from the peer electric car adoption is equal to the sum of the changes in driving, average vehicle emissions, and the number of cars. The impact of driving-related CO_2 emissions is equal to the effect of one new electric car on the average kilometers traveled in the peer group multiplied by the average vehicle emission and the number of cars. Similarly, the impact of CO_2 emission-related changes is equal to the peer effect on the average vehicle emission multiplied by the average kilometer traveled and the number of cars. Finally, the car-related CO_2 emission changes correspond to the peer effect on the number of new cars multiplied by the average vehicle emission and the kilometers traveled.

To empirically estimate the peer effects on the vehicle emissions θ^V, the vehicle kilometers traveled θ^{KM}, and the number of cars θ^N, I regress the individual vehicle emission per kilometer ($\overline{V^{CO_2}_{i,q}}$), the average kilometers traveled ($\overline{KM_{i,q}}$), and the number of cars ($N_{i.q}$) in quarter q on the number of newly registered electric cars in the previous quarter q_{-1} in peer group p, conditional on all individual and peer group characteristics. Equations (D6), (D7), and (D8) state the underlying regression specifications:

$$\overline{V^{CO_2}_{i,q}} = \alpha + \theta^V_q V^e_{p_{-i},q-1} + \gamma \overline{X}_{p_{-i},q} + \delta X_{i,q} + \phi_q + \varepsilon_{i,q}, \tag{D6}$$

$$\overline{KM_{i,q}} = \alpha + \theta^{KM}_q V^e_{p_{-i},q-1} + \gamma \overline{X}_{p_{-i},q} + \delta X_{i,q} + \phi_q + \varepsilon_{i,q}, \tag{D7}$$

$$N_{i.q} = \alpha + \theta^N_q V^e_{p_{-i},q-1} + \gamma \overline{X}_{p_{-i},q} + \delta X_{i,q} + \phi_q + \varepsilon_{i,q}. \tag{D8}$$

As the CO_2 emission model solely changes the outcome of interest, the first stage equation (3) remains unchanged.

D.3. Fossil fuel peer effects

To estimate peer effects from fossil fuel cars, I additionally fit a model for fossil fuel cars f. To construct the SSIV for the adoption of fossil fuel cars, I interact a dummy indicating if the person is at the three-year contract renewal with their estimated propensity to adopt a fossil fuel car in the renewal quarter ($\widehat{Pr}(V^m \mid V^{3y}_{j,q-1} = 1)$). I predict the adoption propensities for fossil fuel cars using the same neural network from equation (2). Then, I construct the propensity-weighted sum of control renewals and the number of new fossil fuel cars as follows:

$$\widehat{V}_{p-1,q-1} = \sum_{j\epsilon N_i} V^{3y}_{j,q-1} \cdot \widehat{Pr}(V^f \mid V^{3y}_{j,q-1} = 1) \tag{D9}$$

$$V^f_{p-1,q-1} = \sum_{j\epsilon N_i} V^f_{j,q-1} \tag{D10}$$

To control for the composition of people's peers and their car preferences, I add a control for the average propensity to lease a new fossil fuel car for all leasing peers within a peer group ($\overline{Pr}(V^f \mid 1V^l_j = 1)_{q,j}$). Accordingly, I fit a first stage equation (D11) and reduced form equation (D12) for fossil fuel cars:

$$V^f_{p-i,q-1} = \alpha^f \widehat{V}_{p-1,q-1} + \delta X_{i,q} + \gamma \overline{X}_{p-i,q} + \delta_2 \overline{Pr}(V^f \mid V^l_j = 1)_{j,q-1} + \phi_q + u_{i,q-1} \tag{D11}$$

$$V^f_{i,q} = \beta^f \widehat{V}_{p-1,q-1} + \delta X_{i,q} + \gamma \overline{X}_{p-i,q} + \delta_2 \overline{Pr}(V^f \mid V^l_j = 1)_{j,q-1} + \phi_q + u_{i,q-1} \tag{D12}$$

The indicator variable $V^f_{i,q}$ captures whether individual i adopts a new fossil fuel car in quarter q. The peer coefficient $\theta^f(\alpha^f/\beta^f)$ measures the effect of the number of new fossil fuel cars in the peer group in the previous quarter on whether the person adopts a new fossil fuel car in the current quarter.

E. Additional peer effect results

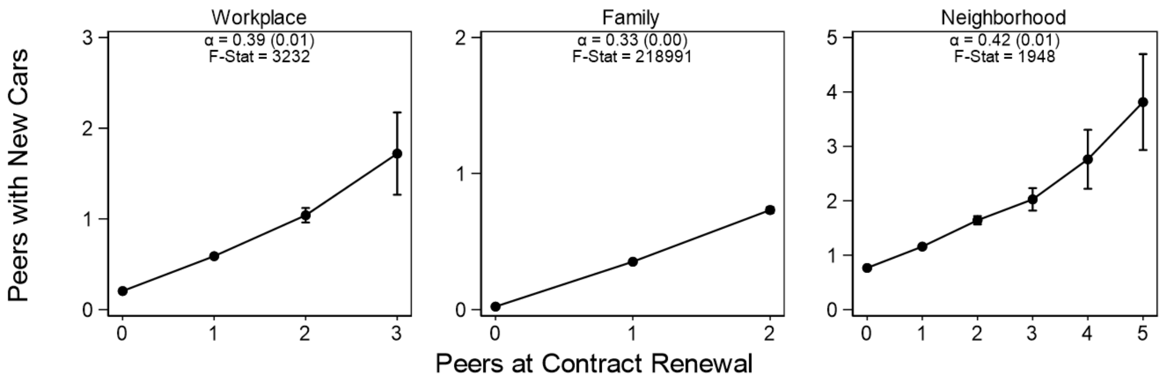

Figure E1: First stage coefficient plots

Notes: The figures present point estimates and 95%-confidence intervals of the first stage in workplaces (Panel A), families (Panel B), and neighborhoods (Panel C) using the contract renewal as an instrument. The y-axis plots peer group new car adoption within bins of peers at the leasing contract renewal. Both relationships are residual of the control variables: individual-demographic variables, peer group characteristics, chargings infrastructure, past car choices, and quarter-fixed effects. The slope coefficients α and the standard errors come from the first stage regression in equation (3). The first stage F-statistics are derived from a peer group level IV regression of the residualized number of new peer electric cars on the number of expiring peer leasing contracts.

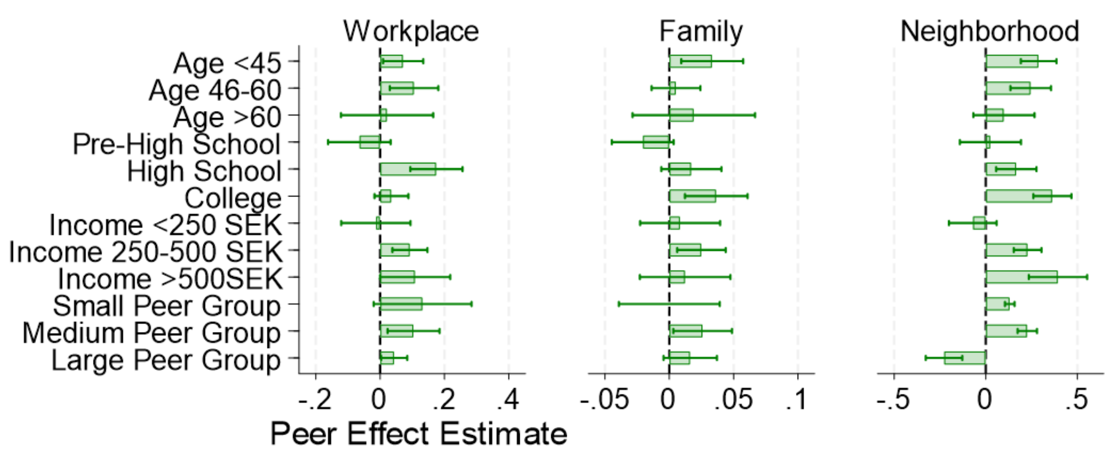

Figure E2: Peer effect heterogeneity by demographic characteristics

Notes: The figures display peer effects, split by demographic characteristics of the peer group, using the propensity-weighted leasing contract renewal instrument in equation (1) for the workplace (Panel A), family (Panel B), and the neighborhood (Panel C). The dependent variable indicates the number of new electric cars in the peer group in a given quarter. 95%-confidence intervals are indicated through the error bars.

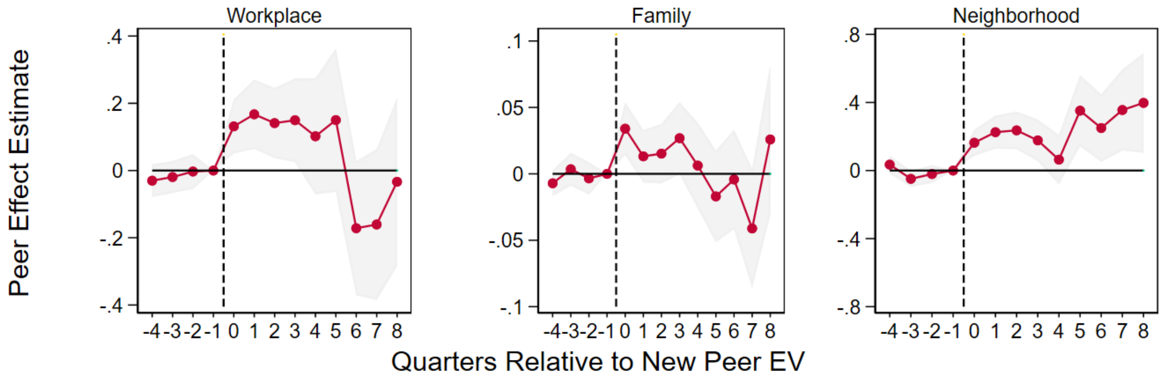

Figure E3: Peer effects for constant groups

Notes: The figure displays the peer effect dynamics for people who remained in the same peer group throughout the entire horizon in the workplace (Panel A), family (Panel B), and neighborhood (Panel C). The dependent variable indicates the number of new electric cars in the peer group in a given quarter. The dashed line between periods -1 and 0 refers to the peer electric car adoption period. The red lines capture the total effect of peer car adoption induced by the leasing contract renewal in quarter q=-1. 95%-confidence intervals reflect robust standard errors, clustered by plants in Panel A, individuals in Panel B, and neighborhoods in Panel C.

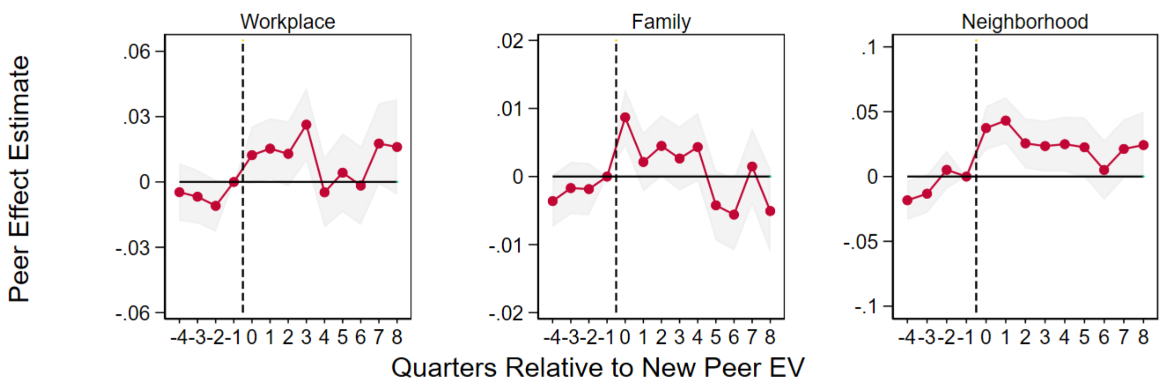

Figure E4: Peer effect dynamics of new cars

Notes: The figure displays the peer effect dynamics for new cars in the workplace (Panel A), family (Panel B), and neighborhood (Panel C). The dependent variable indicates the number of new cars in the peer group in a given quarter. The dashed line between period -1 and 0 refers to the peer car adoption period. The IV coefficients capture the total effect of peer car adoption induced by the leasing contract renewal in quarter q=-1. 95%-confidence intervals reflect robust standard errors, clustered by plants in Panel A, individuals in Panel B, and neighborhoods in Panel C.

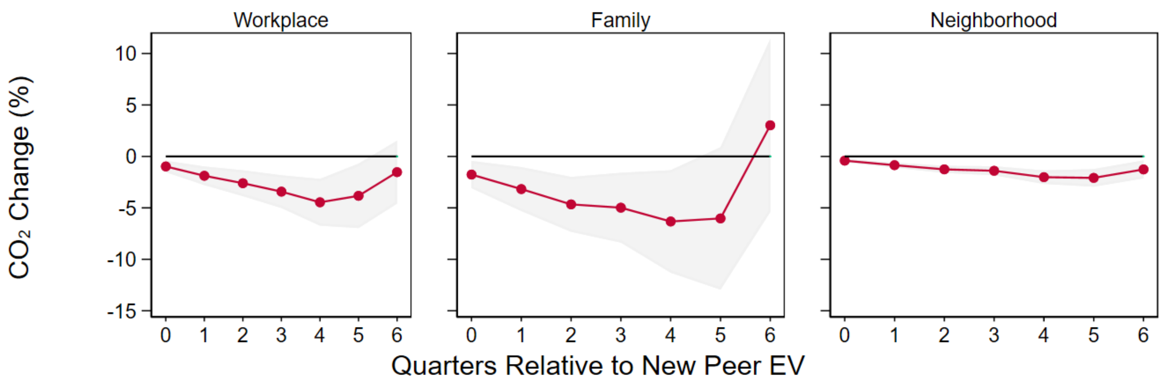

Figure E5: Peer effects on CO_2 emissions

Notes: This figure presents the peer effect of one new electric car on the total CO_2 emission for workplaces (Panel A), families (Panel B), and neighborhoods (Panel C). The dependent variable indicates the total carbon emission normalized to one in quarter zero. All regressions include individual demographic, past car attributes, charging infrastructure, peer group demographic control variables, and quarter-fixed effects. The unit of observation is individual×quarter. The time period reaches from 2012 until 2021. 95%-confidence intervals reflect robust standard errors, clustered by plants in Panel A, individuals in Panel B, and neighborhoods in Panel C.

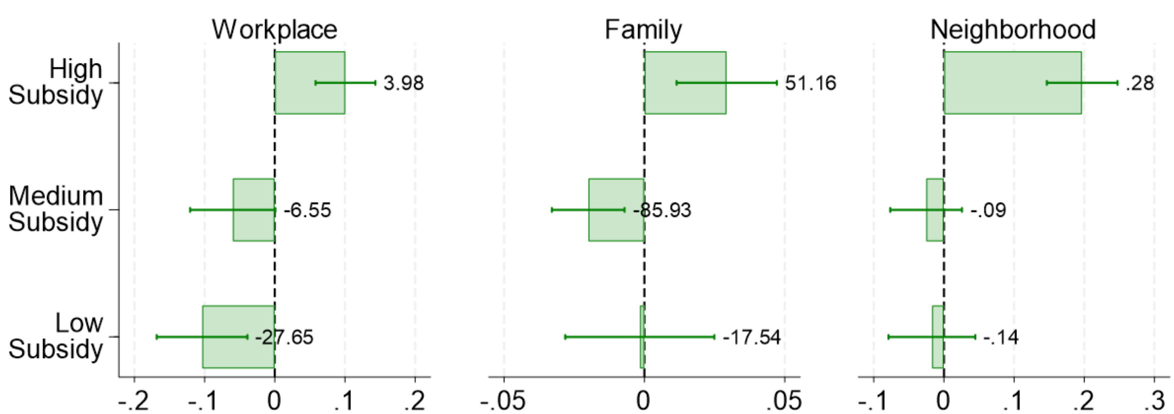

Figure E6: Peer effects for subsidy period

Notes: This figure presents the peer effect results for three different subsidy periods for the workplace (Panel A), family (Panel B), and neighborhood (Panel C). The dependent variable indicates the number of new electric cars in the peer group in a given quarter. I separate the sample into three periods: a low-subsidy period (from January 2012 to June 2018), a medium-subsidy period (July 2018 to December 2019), and a high-subsidy period (from January 2020). The %-effects are reported to the right of the confidence intervals. All regressions include individual demographic, past car attributes, charging infrastructure, peer group demographic control variables, and quarter-fixed effects. The unit of observation is individual×quarter. The time period reaches from 2012 until 2021. 95%-confidence intervals reflect robust standard errors, clustered by plants in Panel A, individuals in Panel B, and neighborhoods in Panel C.

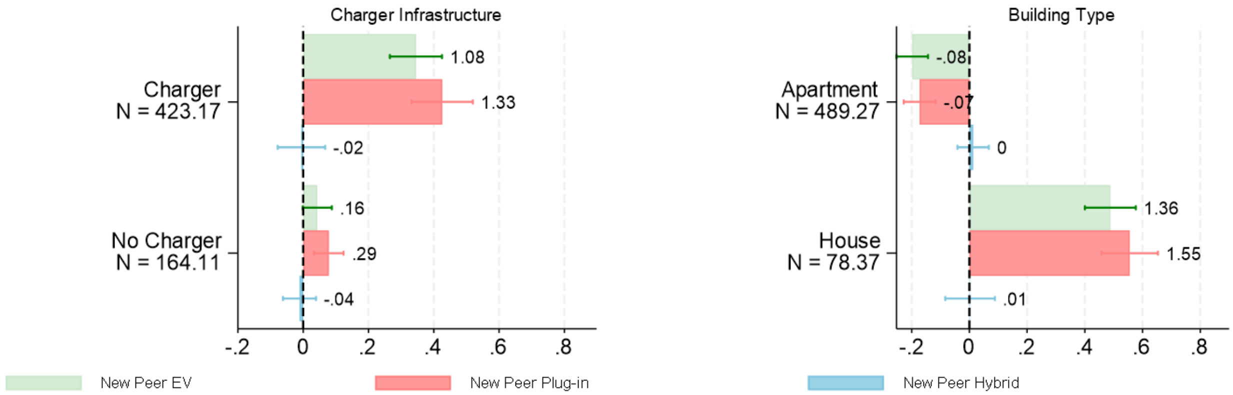

Figure E7: Peer effects by public charger and building type

Notes: This figure presents the peer effect results for electric (green), plug-in (red), and hybrid cars (blue) in neighborhoods for peer groups with and without public charging infrastructure (Panel A), and peer groups living in houses and apartments (Panel B). The dependent variable indicates the number of new electric cars in the peer group in a given quarter. The independent variable measures the number of new electric, plug-in, and hybrid cars in the peer group in the previous quarter. The size of the peer groups is documented along the y-axis. The %-effects are reported to the right of the confidence intervals. All regressions include individual demographic, past car attributes, charging infrastructure, peer group demographic control variables, and quarter-fixed effects. The unit of observation is individual×quarter. The time period reaches from 2012 until 2021. 95%-confidence intervals reflect robust standard errors, clustered by neighborhoods.

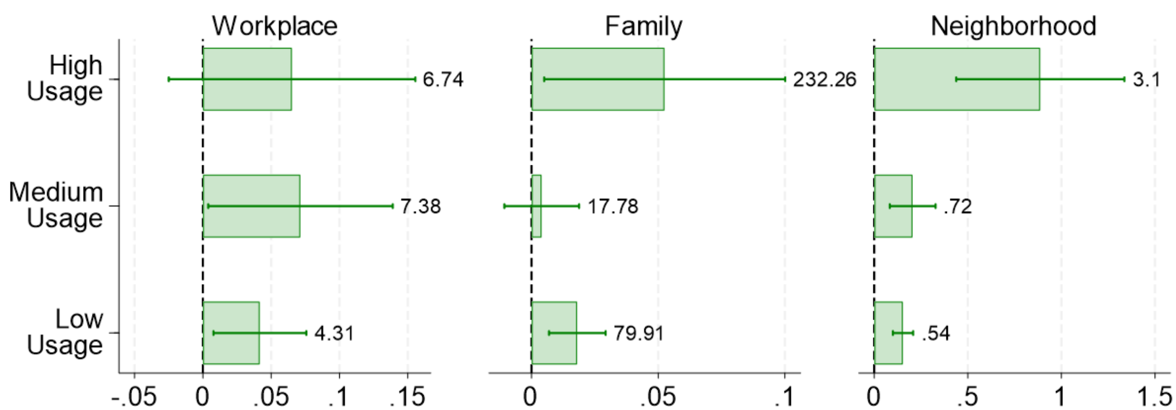

Figure E8: Peer effects by usage

Notes: This figure presents the peer effect results for different levels of usage for the workplace (Panel A), family (Panel B), and neighborhood (Panel C). The dependent variable indicates the number of new electric cars in the peer group in a given quarter. I separate the independent variable into electric cars with three levels of usage: low usage (<8.000km), medium usage (8.000-12.000km), and high usage (>12.000km). The %-effects are reported to the right of the confidence intervals. All regressions include individual demographic, past car attributes, charging infrastructure, peer group demographic control variables, and quarter-fixed effects. The unit of observation is individual×quarter. The time period reaches from 2012 until 2021. 95%-confidence intervals reflect robust standard errors, clustered by plants in Panel A, individuals in Panel B, and neighborhoods in Panel C.

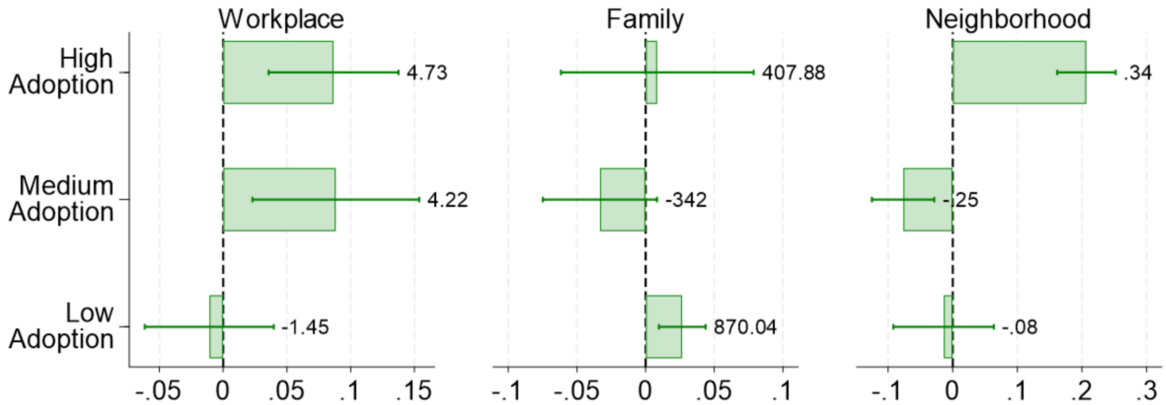

Figure E9: Peer effects by electric car ownership level

Notes: This figure presents the peer effect results for different electric car ownership levels for the workplace (Panel A), family (Panel B), and neighborhood (Panel C). The low, medium, and high categories represent the bottom, middle, and top third of electric car ownership in the respective peer group. The %-effects are reported to the right of the confidence intervals. All regressions include individual demographic, past car attributes, charging infrastructure, peer group demographic control variables, and quarter-fixed effects. The unit of observation is individual×quarter. The time period reaches from 2012 until 2021. 95%-confidence intervals reflect robust standard errors, clustered by plants in Panel A, individuals in Panel B, and neighborhoods in Panel C.

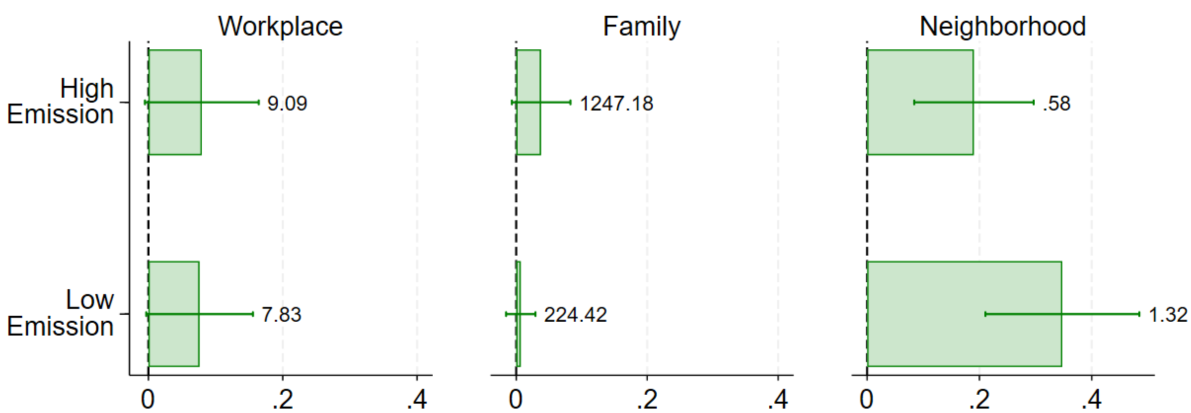

Figure E10: Peer effects by peer group emission

Notes: This figure presents the peer effect results for peer groups with low- and high-carbon emissions of the vehicle fleet for the workplace (Panel A), family (Panel B), and neighborhood (Panel C). The dependent variable indicates the number of new electric cars in the peer group in a given quarter. I split the sample into peer groups with a low and high average carbon-emitting vehicle fleet. All regressions include individual demographic, past car attributes, charging infrastructure, peer group demographic control variables, and quarter-fixed effects. The unit of observation is individual×quarter. The time period reaches from 2012 until 2021. 95%-confidence intervals reflect robust standard errors, clustered by plants in Panel A, individuals in Panel B, and neighborhoods in Panel C.

Table E1: Alternative specifications checks of peer effects

	A. Workplace	B. Family	C. Neighborhood
	(1) 2SLS	(2) 2SLS	(3) 2SLS
Peer Effect Estimate:			
Baseline	.0944***	.0234***	.2240***
	(.0235)	(.0082)	(.0295)
Functional Form:			
Percentage Influence	.1395***	.0036***	1.4979***
	(.0247)	(.0011)	(.1401)
Control Variables:			
Peer Group FE	.0833***	.0220***	.2250***
	(.0236)	(.0085)	(.0297)
Sample Restriction:			
Peer Leasing	.0724**	.0263***	.2733***
	(.0359)	(.0090)	(.0424)
One Peer Lease Renewal	.0943***	.0289*	.2222**
	(.0332)	(.0151)	(.1101)
Network Structure:			
No Overlap	.0744***	.0184***	.2174***
	(.0204)	(.0061)	(.0337)
Control Group:			
Non-Renewal	.1031***	.0526***	.2476***
	(.0240)	(.0082)	(.0318)
Fossil Fuel Car	.1250***	.0601***	.2459***
	(.0246)	(.0083)	(.0298)

Notes: This table presents the regression estimates of peer effects for various alternative specifications in workplaces (Panel A), families (Panel B,) and neighborhoods (Panel C). The dependent variable in columns (1), (2), and (3) indicates the number of new electric cars in the peer group in a given quarter. All regressions include individual demographic, past car attributes, charging infrastructure, peer group demographic control variables, and quarter-fixed effects. The unit of observation is individual×quarter. The time period reaches from 2012 until 2021. Robust standard errors, clustered by plants in Panel A, individuals in Panel B, and neighborhoods in Panel C, are in parentheses. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

Table E2: Varying horizon of peer effects

	Second Stage Horizon			
	(1) 1 Quarter	(2) 2 Quarters	(3) 3 Quarters	(4) 4 Quarters
A.Workplace Network				
New Peer Electric Car	.0947***	.1186***	.1293***	.2347***
	(.0235)	(.0273)	(.0293)	(.0461)
B.Family Network				
New Peer Electric Car	.0234***	.0276***	.0372***	.0102
	(.0082)	(.0092)	(.0135)	(.0096)
C.Neighborhood Network				
New Peer Electric Car	.2242***	.1711***	.1441***	.2476***
	(.0295)	(.0272)	(.0243)	(.0336)

Notes: This table presents the regression estimates of peer effects for varying time horizons in workplaces (Panel A), families (Panel B), and neighborhoods (Panel C). The dependent variable in columns (1), (2), (3), and (4) indicates the number of new electric cars in the peer group in a given quarter, 2-quarters, 3-quarters, and 4-quarters. All regressions include individual demographic, past car attributes, charging infrastructure, peer group demographic control variables, and quarter-fixed effects. The unit of observation is individual×quarter. The time period reaches from 2012 until 2021. Robust standard errors, clustered by plants in Panel A, individuals in Panel B, and neighborhoods in Panel C, are in parentheses. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

Table E3: Varying machine learning techniques

	Machine Learning Prediction		
	(1) Logistic	(2) Lasso	(3) Random Forrest
A.Workplace Network			
New Peer Electric Car	.1249***	.1081***	.0627**
	(.0273)	(.0226)	(.0263)
B.Family Network			
New Peer Electric Car	.0489***	.0366***	.0103**
	(.0128)	(.0107)	(.0045)
C.Neighborhood Network			
New Peer Electric Car	.1979***	.2016***	.1237***
	(.0298)	(.0233)	(.0440)

Notes: This table presents the regression estimates of peer effects for alternative predictions of exposure shares in workplaces (Panel A), families (Panel B), and neighborhoods (Panel C). Columns (1), (2), and (3), present the second stage estimation using a logistic regression, a LASSO regression, and a random forrest to predict the propensity of electric car adoption at the renewal threshold.The dependent variable indicates the number of new electric cars in the peer group in a given quarter. All regressions include individual demographic, past car attributes, charging infrastructure, peer group demographic control variables, and quarter-fixed effects. The unit of observation is individual×quarter. The time period reaches from 2012 until 2021. Robust standard errors, clustered by plants in Panel A, individuals in Panel B, and neighborhoods in Panel C, are in parentheses. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

Table E4: Peer effects for placebo peer groups

	OLS	First Stage	Second Stage	
	(1)	(2)	(3) Total	(4)Per Capita
A.Workplace Network				
Firm Co-worker	-.0127***	7.8709***	-.0541	-.0001
	(.0037)	(1.9308)	(.0884)	(.0002)
Mean Dep. Variable	.154	.154	.154	.154
Future Co-worker	.0005	1.1995***	.0071	.0007
	(.0006)	(.1925)	(.0243)	(.0022)
Mean Dep. Variable	.005	.005	.005	.005
C.Neighborhood Network				
Future Neighbor	.0014	1.2396***	.0168	.0002
	(.0012)	(.1594)	(.0421)	(.0004)
Mean Dep. Variable	.041	.041	.041	.041

Notes: This table presents the regression estimates of peer effects for placebo peer groups in workplaces (Panel A) and neighborhoods (Panel C) using the contract renewal timing instrument. Column (1) presents OLS estimates from the regression in equation (1), column (2) equals the first stage estimation of equation (3), and column (3) and (4) reflect the second stage estimation. The dependent variable in columns (1), (2), and (3) indicates the number of new electric cars in the peer group in a given quarter. The dependent variable in column (4) divides the total effects by the size of the peer group, which gives an estimate of the peer effect "per capita." The placebo co-workers are: 1. Firm-level co-workers: Individuals employed in the same firm, two-digit industry, and region, but who do not work in the same plant; 2. Future co-workers: Individuals who switch into the same workplace in the future. The placebo neighbors are future neighbors that move into the same neighborhood. All regressions include individual demographic, past car attributes, charging infrastructure, peer group demographic control variables, and quarter-fixed effects. The unit of observation is individual×quarter. Robust standard errors, clustered by plants in Panel A, individuals in Panel B, and neighborhoods in Panel C, are in parentheses. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

Table E5: Peer effects for new cars

	OLS	Second Stage	
	(1)	(2) Total	(3) Per Capita
A.Workplace Network			
New Peer Car	.0384***	.0123*	.0003*
	(.0027)	(.0067)	(.0001)
%-Effect	.41	.13	.13
Mean Dep. Variable	.209	.209	.209
B.Family Network			
New Peer Car	.0110***	.0087***	.0012***
	(.0002)	(.0021)	(.0003)
%-Effect	4.89	3.88	3.88
Mean Dep. Variable	.031	.031	.031
C.Neighborhood Network			
New Peer Car	.0305***	.0374***	.0001***
	(.0015)	(.0086)	(.0000)
%-Effect	.01	.01	.01
Mean Dep. Variable	1.063	1.063	1.063

Notes: This table presents the regression estimates of peer effects for all new cars in workplaces (Panel A), families (Panel B), and neighborhoods (Panel C). Column (1) presents OLS estimates from the regression, columns (2) and (3) reflect the second stage estimation using the contract renewal instrument. The dependent variable in columns (1), and (2) indicates the number of new cars in the peer group in a given quarter. The dependent variable in column (3) divides the total effects by the size of the peer group, which gives an estimate of the peer effect "per capita." All regressions include individual demographic, past car attributes, peer group demographic control variables, and quarter-fixed effects. The %-effects and the mean dependent variables are reported below the coefficients. The unit of observation is individual×quarter. The time period reaches from 2012 until 2021. Robust standard errors, clustered by plants in Panel A, individuals in Panel B, and neighborhoods in Panel C, are in parentheses. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

Table E6: Peer effects by EV type

	Electric Vehicle Type		
	(1) Hybrid	(2) Plug-In & Battery	(3) Any Electric
A.Workplace Network			
New Peer Hybrid Car	.0489	-.2887***	-.2398***
	(.0369)	(.0693)	(.0774)
New Peer Plug-In Car	-.0187***	.1988***	.1801***
	(.0032)	(.0382)	(.0380)
Mean Dep. Variable	.006	.015	.021
B.Family Network			
New Peer Hybrid Car	-.0045	-.0226***	-.0271***
	(.0049)	(.0074)	(.0089)
New Peer Plug-In Car	-.0015**	.0341***	.0327***
	(.0007)	(.0094)	(.0094)
Mean Dep. Variable	.001	.002	.003
C.Neighborhood Network			
New Peer Hybrid Car	.0542	-.0293	.0248
	(.0465)	(.0383)	(.0610)
New Peer Plug-In Car	-.0529***	.8435***	.7906***
	(.0068)	(.0787)	(.0775)
Mean Dep. Variable	.036	.073	.109

Notes: This table presents the peer effect results for hybrid and plug-in electric cars for the workplace (Panel A), family (Panel B), and neighborhood (Panel C). The dependent variable indicates the number of new hybrid (column 1), plug-in (column 2), and all new cars (column 3) in the peer group. The independent variable measures the number of new hybrid and plug-in cars in the peer group in the previous quarter. All regressions include individual demographic, past car attributes, charging infrastructure, peer group demographic control variables, and quarter-fixed effects. The unit of observation is individual×quarter. The time period reaches from 2012 until 2021. Robust standard errors, clustered by plants in Panel A, individuals in Panel B, and neighborhood in Panel C, are in parentheses. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

Table E7: Alternative outcomes of peer effects

	Vehicle Ownership			Second-Hand
	(1)Weight	(2)Engine	(3)Fuel	(4) Electric
A.Workplace Network				
New Peer Electric Car	-3.822	-1.218*	-0.118***	0.012
	(9.686)	(0.707)	(0.039)	(0.016)
Mean Dep. Variable	643.7	44.79	2.63	.019
B.Family Network				
New Peer Electric Car	-39.038***	-3.338***	-.130**	.003
	(14.972)	(1.121)	(.066)	(.006)
Mean Dep. Variable	611.81	42.38	2.49	.002
C.Neighborhod Network				
New Peer Electric Car	-5.883**	-.658***	-.071***	.024
	(2.393)	(.182)	(.011)	(.019)
Mean Dep. Variable	590.01	40.82	2.41	.094

Notes: This table presents the regression estimates of peer effects on three car characteristics for workplaces (Panel A), families (Panel B), and neighborhoods (Panel C). The outcome of interest is equal to three average car characteristics per person one year after the peer electric car adoption: (1) weight [kilogram], (2) engine power [kilowatt], and (3) fuel efficiency [liter/100km]. All regressions include individual demographic, past car attributes, charging infrastructure, peer group demographic control variables, and quarter-fixed effects. The unit of observation is individual×quarter. The time period reaches from 2012 until 2021. Robust standard errors, clustered by plants in Panel A, individuals in Panel B, and neighborhoods in Panel C, are in parentheses. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

Table E8: Peer effects in leasing contracts

	Lease Contracts			Purchases
	(1) New	(2) Expiring	(3) Early	(4) New
A.Workplace Network				
New Peer Electric Car	.0233*	.0073	.0125	.0174
	(.0142)	(.0055)	(.0077)	(.0115)
Mean Dep. Variable	.009	.001	.001	.01
B.Family Network				
New Peer Electric Car	.0218***	.0024	.0040	-.0006
	(.0067)	(.0024)	(.0027)	(.0040)
Mean Dep. Variable	.001	0	0	.002
C.Neighborhood Network				
New Peer Electric Car	.1513***	.0477***	.0399***	.0489***
	(.0218)	(.0101)	(.0089)	(.0158)
Mean Dep. Variable	.039	.007	.005	.058

Notes: This table presents the regression estimates of peer effects for different leasing contract renewals in workplaces (Panel A), families (Panel B), and neighborhoods (Panel C). The dependent variables in columns (1), (2), and (3) indicate the number of new electric cars with a new leasing contract, at the three-year leasing renewal, and renewed before the leasing renewal, respectively. Column (4) refers to new electric car purchases. All regressions include individual demographic, past car attributes, charging infrastructure, peer group demographic control variables, and quarter-fixed effects. The mean dependent variables is reported below the coefficients. The unit of observation is individual×quarter. The time period reaches from 2012 until 2021. Robust standard errors, clustered by plants in Panel A, individuals in Panel B, and neighborhoods in Panel C, are in parentheses. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

Table E9: Fossil fuel peer effects

	Vehicle Type		
	(1) Fossil	(2) Electric	(3) New Cars
A.Workplace Network			
New Peer Fossil Car	.0135	-.1137***	-.0987**
	(.0365)	(.0229)	(.0416)
Mean Dep. Variable	.188	.021	.21
B.Family Network			
New Peer Fossil Car	.0613***	-.0916***	-.0307
	(.0231)	(.0211)	(.0308)
Mean Dep. Variable	.027	.003	.031
C.Neighborhood Network			
New Peer Fossil Car	.3185	-.3112**	-.3270
	(.2633)	(.1365)	(.2083)
Mean Dep. Variable	.95	.109	1.063

Notes: This table presents the peer effect results for fossil fuel cars for the workplace (Panel A), family (Panel B), and neighborhood (Panel C). The dependent variable indicates the number of new fossil fuel (column 1), electric (column 2), and all new cars (column 3) in the peer group. The independent variable measures the number of new fossil fuel cars in the peer group in the previous quarter. All regressions include individual demographic, past car attributes, charging infrastructure, peer group demographic control variables, and quarter-fixed effects. The underlying regression specification for peer effects in fossil fuel cars is documented in Section D.3. The unit of observation is individual×quarter. The time period reaches from 2012 until 2021. Robust standard errors, clustered by plants in Panel A, individuals in Panel B, and neighborhood in Panel C, are in parentheses. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

F. Details on optimal peer effect subsidy

F.1. Proof of proposition 1.

I assume that the choice of car is influenced by *i.i.d.* random variables ε^e and ε^f drawn from a common extreme value distribution with zero expected value and standard deviation proportional to a scale parameter μ. Define the utilities as:

$$U^f = W^f + \varepsilon^f,$$

$$U^e = W^e + \varepsilon^e.$$

A consumer selects the fossil fuel car if $U^f > U^e$, occurring with probability

$$\pi \equiv Pr(U^f > U^e) = \frac{exp(\frac{W^f}{\mu})}{exp(\frac{W^f}{\mu}) + exp(\frac{W^e}{\mu})}.$$

The expected utility of a new car purchase is given by:

$$E[max[U^e, U^f]] = \mu ln(exp(\frac{W^f}{\mu}) + exp(\frac{W^e}{\mu})).$$

Let $\Phi^f = \phi^f KM^f$ and $\Phi^e = \phi^e KM^e$, where ϕ^f and ϕ^e are the sum of unincorporated marginal externalities (in \$ per kilometer) from driving a fossil fuel and electric car car. Let $F = \pi KM^f$, $E = (1-\pi)KM^e$, and $H = (1-\pi)KM^f$. Suppose a policymaker optimizes the welfare function given in equation (9) by setting a subsidy τ for electric cars. Taking the derivative of $\mathcal{W}$ with respect to τ:

$$\frac{\partial \mathcal{W}}{\partial \tau} = (1-\pi) + \frac{\partial R}{\partial \tau} + -(\phi^f(\frac{\partial F}{\partial \tau} + \frac{\partial H}{\partial \tau}\theta^f) + \phi^e \frac{\partial E}{\partial \tau}(1+\theta^e)) = 0.$$

Given that expected tax revenue is $R = -\tau(1-\pi)$, we have:

$$\frac{\partial R}{\partial \tau} = -(1-\pi) + \tau \frac{\partial \pi}{\partial \tau}.$$

Substituting this into the first-order condition:

$$\tau \frac{\partial \pi}{\partial \tau} - ((\phi^f(\frac{\partial F}{\partial \tau} + \frac{\partial H}{\partial \tau}\theta^f) + \phi^e \frac{\partial E}{\partial \tau}(1+\theta^e)) = 0.$$

Solving for τ:

$$\tau = \frac{\phi^f(\frac{\partial F}{\partial \tau} + \frac{\partial H}{\partial \tau}\theta^f) + \phi^e \frac{\partial E}{\partial \tau}(1+\theta^e)}{\frac{\partial \pi}{\partial \tau}}.$$

Taking the derivative of F, E, and H, we have:

$$\frac{\partial F}{\partial \tau} = \frac{\partial KM^f}{\partial \tau}\pi + KM^f \frac{\partial \pi}{\partial \tau} = KM^f \frac{\partial \pi}{\partial \tau},$$
$$\frac{\partial E}{\partial \tau} = \frac{\partial KM^e}{\partial \tau}(1-\pi) - KM^e \frac{\partial \pi}{\partial \tau} = -KM^e \frac{\partial \pi}{\partial \tau},$$
$$\frac{\partial H}{\partial \tau} = \frac{\partial KM^f}{\partial \tau}(1-\pi) - KM^f \frac{\partial \pi}{\partial \tau} = -KM^f \frac{\partial \pi}{\partial \tau},$$

where the second equality follows from the fact that there are no income effects (i.e., $\frac{\partial KM^f}{\partial \tau} = \frac{\partial KM^e}{\partial \tau} = 0$). Substituting these into the first-order condition for τ and let $\Phi^f = \phi^f KM^f$ and $\Phi^e = \phi^e KM^e$, we have:

$$\tau^* = \underbrace{\Phi^f - \Phi^e}_{\triangle Marginal\ Externalities} - \underbrace{\Phi^f\theta^f - \Phi^e\theta^e}_{\triangle Peer\ EVs}$$

■

F.2. Peer effects in fossil fuel cars

In addition to the peer effects in electric car adoption, the policymaker may also incorporate how peer effects in fossil fuel car adoption affect the subsidy τ on electric cars. The peer effects in fossil fuel car adoption measures how one new fossil fuel car influences new fossil fuel (θ^f_f) and electric car acquisitions (θ^e_f) in the peer group (Table E9). The subscript refers to the vehicle adoption of peers, the superscript refers to persons' own vehicle adoption. To incorporate peer effects in both electric and fossil fuel car adoptions, the policymaker optimizes the welfare function given by:

$$\begin{aligned}\mathcal{W}^f &= \mu(ln(exp(\frac{W^e}{\mu}) + exp(\frac{W^f}{\mu}))) + R - (\pi(\Phi^f(1+\theta^f_f) + \Phi^e\theta^e_f) \\ &+ (1-\pi)(\Phi^e(1+\theta^e) + \Phi^f\theta^f)). \end{aligned} \tag{F1}$$

Following the same steps as outlined above, we derive the following proposition that incorporates the peer-induced externality changes of fossil fuel cars:

Proposition 2. *The second-best subsidy for electric cars that internalizes how peer effects in electric and fossil fuel car adoption influence the subsequent acquisition of electric and fossil fuel cars is given*

$$\tau^f = \underbrace{\Phi^f - \Phi^e}_{\triangle Marginal\ Externalities} - \underbrace{\Phi^f\theta^f - \Phi^e\theta^e}_{\triangle Peer\ EVs} + \underbrace{\Phi^f\theta^f_f + \Phi^e\theta^e_f}_{\triangle Peer\ Fossil}$$

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