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Hydrogen infrastructure, fuel cell electric vehicles, and indirect network effects: Evidence from Japan*

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Abstract

Contrary to expectations in business and policy circles, progress in the adoption of fuel cell electric vehicles (FCEVs) and the expansion of hydrogen charging stations (HCSs) has been slow in developed countries, raising concerns about the viability of hydrogen mobility. To address this challenge, this study examines the indirect network effects in Japan's FCEV market. We estimate the impact of HCS deployment on FCEV adoption using vehicle registration data from 2013 to 2020 and a staggered difference-in-differences research design. Additionally, we assess the effect of FCEV stock on HCS deployment using a system generalized method of moments estimator in a dynamic panel model. The results indicate positive and statistically significant indirect network effects on both sides of the market; however, the size of the network effects remains insufficient to generate positive feedback loops. Weak indirect network effects are also reflected in event-study results, demonstrating that the effect of HCS deployment on FCEV adoption diminishes over time. Our study suggests that developing HCS networks at an early stage is financially unsustainable without strong demand-side growth. This study broadens the understanding of zero-emission vehicle markets by providing the first evidence on indirect network effects in the FCEV market, while highlighting key distinctions from the battery electric vehicle market.

Keywords: fuel cell electric vehicles, hydrogen charging station, indirect network effects, staggered difference-in-differences, Japan

JEL classification: Q42, L14, L62

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1. Introduction

Decarbonizing road transport through electrification has become an important strategy for reducing vehicular emissions (International Energy Agency, 2023). Electrified vehicles include battery electric vehicles (BEVs), fuel cell electric vehicles (FCEVs), plug-in hybrid electric vehicles (PHEVs), and hybrid electric vehicles (HEVs). Each type has unique advantages, complementing one another to create a robust, flexible, and sustainable transition away from internal combustion engine vehicles while addressing various transportation needs. Initially, PHEVs and HEVs served as intermediate steps toward full electrification. However, with advancements in infrastructure, technology, and renewable energy integration, BEVs and FCEVs are expected to dominate the long-term vehicle market, offering zero-emission solutions for diverse applications (International Energy Agency, 2023).

The zero-emission vehicle market (BEVs and FCEVs) is characterized by indirect network effects, where the value of vehicles depends on the availability of charging or refueling infrastructure and vice versa. This dynamic creates a "chicken and egg" problem: consumers are hesitant to buy zero-emission vehicles due to a lack of infrastructure, while infrastructure companies are reluctant to invest due to insufficient demand. Indirect network effects are particularly influential in infant markets, such as those for zero-emission vehicles, as they introduce the possibility of lock-in, resulting in the failure of new technology (Greaker and Heggedal, 2010; Meunier and Ponssard, 2020; Zhou and Li, 2018). Thus, a thorough understanding of indirect network effects is crucial for formulating effective policies for developing zero-emission vehicle markets.

Extensive research has examined indirect network effects in BEV markets. Using quarterly panel data covering 17 car models and 353 Metropolitan Statistical Areas in the United States, Li et al. (2017) identified indirect network effects on both sides of the market and demonstrated that subsidizing charging station deployment is more effective than subsidizing vehicle sales. Similarly, Springel (2021) analyzed the Norwegian BEV market and reached comparable conclusions. Subsequent studies have confirmed the effectiveness of charging station deployment in promoting BEV adoption in China (Kalthaus and Sun, 2021), Norway (van Dijk et al., 2022), and France (Haidar and Rojas, 2022). By contrast, research on these effects in FCEV markets remains limited.

This study addresses this gap by examining the indirect network effects in Japan's FCEV passenger car market.[2] Japan's FCEV market offers a unique context as it introduced the world's first FCEV, the Toyota Mirai, in 2014. The government has also set ambitious hydrogen mobility targets, aiming to register 800,000 FCEVs and deploy 900 hydrogen charging stations (HCSs) by 2030 (Ministry of Economy, Trade and Industry, 2019). However, adoption remains limited, with approximately 8,000 FCEVs and 160 HCSs deployed as of 2024, despite generous financial incentives (Next Generation Vehicle Promotion Center, 2025). The divergence between policy targets and realized adoption rates raises concerns over how much, or even whether, indirect network effects exist in Japan's FCEV market and the cost-effectiveness of subsidies for FCEV adoption and HCS deployment. Evaluating these effects in Japan offers valuable policy insights for not only Japan but also European countries and the United States (especially California), which face similar challenges (Element Energy, 2024).

[2] Trucks, buses, and special purpose vehicles (e.g., ambulances) are excluded from this study due to the absence or limited number of registrations. Unless otherwise stated, FCEVs refer exclusively to passenger cars.

We estimate the effect of HCS deployment on FCEV adoption in Japan using administrative data on vehicle registrations from 2013 to 2020. A staggered difference-in-differences (DD) approach exploits variations in the timing of the first HCS deployment across municipalities. A matching approach constructs a control group based on propensity scores derived from municipal characteristics before HCS deployment, and Callaway and Sant'Anna's (2021) method is applied to account for heterogeneous treatment effects. Next, we estimate the effect of FCEV stock on HCS deployment using a system generalized method of moments (GMM) estimator to a dynamic panel model.

Our analyses reveal several important insights. Consistent with Li et al. (2017) and Springel (2021), our findings confirm the existence of indirect network effects in Japan's FCEV market in both directions: HCS deployment promotes FCEV adoption, and an increase in FCEV stock drives further HCS deployment. Specifically, our DD estimates suggest that HCS deployment increased the probability of FCEV adoption by 0.09 percentage points during the post-HCS deployment period for residents inside municipalities with HCS compared to those without. GMM estimates suggest that an increase of 500 FCEV stocks in a municipality leads to the deployment of an additional HCS. Our results remain robust across various specifications, placebo tests, and estimation techniques and show no spillover effects of HCS deployment to neighboring non-HCS municipalities, alleviating identification concerns.

Using these estimates, we examine the potential increase in FCEV adoption if the government achieves its target of 900 HCSs, equivalent to each treated municipality in our sample installing six additional HCSs. One significant finding is that the magnitude of indirect network effects remains too small to generate positive feedback loops between

FCEV adoption and HCS deployment, even under large-scale HCS deployment scenarios. This contrasts with BEV markets, as observed by Li et al. (2017) and Springel (2021). Weak indirect network effects are also reflected in event-study results, demonstrating that the effect of HCS deployment on FCEV adoption diminishes over time, unlike the increasing effects observed in BEV markets (van Dijk et al., 2022). This weak response among early adopters could stem from the high FCEV purchase and operating costs, low awareness, and insufficient incentive schemes. Our preliminary calculation suggests that FCEV registrations per HCS increase by only 11, implying that each additional FCEV adoption driven by HCS deployment costs approximately US$ 305,000.

Our study addresses two strands of literature. The first pertains to the broad literature that empirically analyzes indirect network effects. Previous studies have examined indirect network effects in two-sided markets, such as CD titles and players (Gandal et al., 2000), PDA devices and compatible software (Nair et al., 2004), Yellow Pages directories (Rysman, 2004), video games (Clements and Ohashi, 2005; Corts and Lederman, 2009; Lee, 2013), broadcasting (Crawford and Yurukoglu, 2012), and news media (Gentzkow et al., 2014). More recent studies have explored indirect network effects in markets for low- and zero-emission vehicles, such as flex-fuel vehicles (Corts, 2010; Shriver, 2015) and BEVs and PHEVs (Haidar and Rojas, 2022; Kalthaus and Sun, 2021; Li et al., 2017; Springel, 2021; van Dijk et al., 2022). This study broadens the understanding of zero-emission vehicle markets by providing the first empirical evidence on indirect network effects in the FCEV market, while highlighting key distinctions from the BEV market.

Second, this study adds to the literature on the role of HCSs in determining FCEV adoption. By analyzing survey data from Aichi Prefecture in Japan, Khan et al. (2020,

2021) found that HCS availability significantly influences both potential buyers' adoption decisions and early adopters' continued usage. Similarly, Kelley et al. (2020, 2022) and Stotts et al. (2021) analyzed survey data from California in the United States, highlighting the influence of HCS locations in early adopters' decisions. For example, most early adopters require at least one conveniently located HCS along frequently traveled routes. This study adds to the survey-based literature by providing the first empirical evidence on early adopters' responses to HCS development using a quantitative approach.

Large-scale HCS networks are widely regarded as vital for expanding the FCEV market early. Similar to Japan, California aims to deploy 1,000 HCSs by 2030 (44 as of November 2024) to promote hydrogen mobility (California Fuel Cell Partnership, 2018). Hydrogen Mobility Europe targets 1,000 public HCSs across Europe by 2025 (168 as of January 2024) (Element Energy, 2024). Our study suggests that developing HCS networks on such a large scale is expensive and financially unsustainable without strong demand-side growth. This underscores the need for fundamental reforms in hydrogen mobility strategies, with more emphasis on demand-side measures such as reducing upfront and operating costs of FCEV adoption, increasing public awareness, and offering additional incentives (e.g., free public transport, toll exemption, and free public parking).

The remainder of this paper is structured as follows. Section 2 provides background information on FCEVs, HCSs, and Japan's policy context. Section 3 describes the data and sample used in the study. In Section 4, we present the empirical approaches for estimating indirect network effects. Section 5 presents empirical evidence on the effects of HCS deployment on FCEV adoption, the effects of FCEV stock on HCS deployment, and a discussion on policy implications. Section 6 concludes.

2. Background

2.1. FCEVs

FCEVs are electric vehicles that use hydrogen as their primary fuel source (Hassan et al., 2023; Soleimani et al., 2024). Hydrogen gas from high-pressure storage tanks is fed into the fuel cell stack, where it undergoes an electrochemical reaction with oxygen from the air. This process splits hydrogen molecules into protons and electrons at the anode. The protons pass through an electrolyte membrane to the cathode, whereas the electrons travel through an external circuit, generating an electric current that powers the vehicle's onboard electric motor, which drives the wheels. At the cathode, protons, electrons, and oxygen combine to form water, which is released as the only emission, making FCEVs zero-emission vehicles.

The first FCEV prototype, the Chevrolet Electrovan, was introduced by General Motors in 1966, inspired by the hydrogen fuel cells used in the Apollo spacecraft.[3] The project was eventually scrapped because of several challenges, including high costs, safety concerns with pressurized tanks, and a lack of hydrogen infrastructure. Decades later, several carmakers introduced lease-only FCEVs, including the Toyota FCHV and Honda FCX in 2002 and the Hyundai ix35 FCEV in 2013. In 2014, Toyota launched the Mirai, recognized as the world's first mass-produced FCEV, followed by the Honda Clarity in 2016 and the Hyundai Nexo in 2018.

FCEVs offer key advantages over BEVs, particularly, faster refueling times and longer driving ranges. For example, the Toyota Mirai takes approximately 3 min to fill its 5.6 kg hydrogen tank, providing an 850 km driving range (Toyota Motor Corporation, 2024),

[3] See Corby (2021) for more details on the history of FCEVs.

comparable to gasoline vehicles such as the Toyota Corolla Sport. By contrast, a comparable BEV, such as the Nissan Leaf (60 kWh battery), takes approximately 60 min to recharge 80% of its battery capacity even with a fast-charging station, offering a 500 km driving range (Nissan Motor Corporation, 2024).

However, despite these advantages, the widespread adoption of FCEVs remains limited, largely due to high purchase costs and infrastructure constraints. The gross price of the Toyota Mirai is approximately US$ 52,000, but national government incentives, such as subsidies and tax cuts, reduce the net purchasing price to US$ 40,000. Additional municipal subsidies can further lower purchasing costs, as seen in Tokyo, where the final price drops to US$ 32,000. Despite generous financial support, FCEVs remain 35–47% more expensive than other electrified vehicles; in Tokyo, the final prices for the Nissan Leaf (BEV) and Toyota Corolla Sport (HEV) are US$ 21,000 and US$ 17,000, respectively. The higher costs of FCEVs stem from expensive fuel cell components, hydrogen storage systems, and limited economies of scale in production.

2.2. HCSs

HCSs are categorized into three types: on-site, off-site, and portable. On-site stations produce hydrogen on-site using city gas or liquefied petroleum gas. Off-site stations rely on hydrogen delivered from external production facilities via trailers instead of on-site hydrogen production. Portable stations comprise large trucks carrying the necessary hydrogen refueling equipment (e.g., a hydrogen cylinder bundle, compressor, hydraulic accumulator, and dispenser) to refuel an FCEV at a predetermined location. As of 2023, on-site, off-site, and portable stations accounted for 17%, 58%, and 25% of Japan’s total HCSs, respectively.

Given the high costs and technical expertise required for HCS operation, these stations are primarily managed by oil, industrial gas, and city gas companies. Among them, the largest operator is the Iwatani Corporation, operating 53 HCSs across the country, followed by ENEOS (43) and Air Liquide Japan (17). Entering the HCS business is costly; constructing an off-site HCS costs approximately US$ 3.3 million—five times greater than that of a standard gasoline station—due to highly specialized equipment, including pressure accumulators, compressors, dispensers, and freezing machines, as well as precision engineering. Annual operating costs for an off-site HCS amount to US$ 220,000, also exceeding those of a gasoline station. To encourage HCS deployment, the national government subsidizes two-thirds of construction and operation costs, regardless of station size or type.

In February 2018, Japan H_2 Mobility (JHyM) was established by private companies, including HCS companies, automobile manufacturers, and financial investors, to facilitate the effective and strategic deployment of HCSs, particularly in four major metropolitan areas: Tokyo, Osaka, Nagoya, and Fukuoka. JHyM developed an optimal station placement map to ensure accessibility within 15 min and introduced measures to extend HCS operation hours. Additionally, JHyM streamlines subsidy applications and offers supplementary financial support, further reducing HCS construction and operational costs.

Given that HCSs handle highly pressurized hydrogen, a flammable gas, their construction and operation are highly regulated. For example, the Building Standards Act bans HCS construction in certain residential and industrial districts, while the High Pressure Gas Safety Act mandates that at least one certified high-pressure gas safety supervisor be present during station operation.

2.3. Hydrogen and fuel cell strategy

In December 2013, the Ministry of Economy, Trade and Industry (METI) established the Hydrogen and Fuel Cell Strategy Council to promote the widespread use of hydrogen energy and fuel cell technology in Japan. The council focuses on four key areas: (a) establishing a hydrogen supply chain, (b) promoting hydrogen utilization, (c) fostering technological development, and (d) enhancing public awareness. To ensure progress in these areas, the council announced the Hydrogen and Fuel Cell Strategy (HFCS) in June 2014, setting specific targets and timelines (Ministry of Economy, Trade and Industry, 2019). This strategy was later revised in 2016 and 2019 to reflect progress and changing domestic and international conditions.

FCEVs form an important component of the HFCS for several reasons. First, road transport accounted for 16% of Japan's total carbon dioxide emissions in 2022, with passenger cars contributing 52% of road transport emissions, followed by trucks at 44% (Ministry of Land, Infrastructure, Transport and Tourism, 2025). Adopting zero-emission vehicles, including FCEVs, is considered to be a promising pathway to decarbonize road transport. Second, the diffusion of FCEVs balances electricity demand by reducing reliance on BEVs and PHEVs, particularly during peak charging periods that could strain the power grid. Third, widespread FCEV adoption can drive investments in hydrogen production, infrastructure, and distribution, potentially creating new industries, generating job opportunities, and fostering technological innovation (Soleimani et al., 2024).

The HFCS targeted 40,000 FCEV registrations by 2020, 200,000 by 2025, and 800,000 by 2030, respectively (Ministry of Economy, Trade and Industry, 2019).[4] However, the actual rollouts have fallen far below the targets. Table 1 shows that by 2024, FCEV registrations were limited to 7,748, approximately 32,000 below the 2020 target. Achieving the 2025 and 2030 targets would require an additional 192,000 and 792,000 registrations, respectively. It is also evident that compared with other electrified vehicles, the diffusion process of FCEVs has been notably sluggish.

Table 1
Registrations of electrified vehicles in Japan

	FCEVs	BEVs	PHEVs	HEVs
2014		38,794	30,171	3,823,057
2015	150	52,639	44,012	4,684,755
2016	630	62,134	57,130	5,558,725
2017	1,807	73,378	70,323	6,544,268
2018	2,440	91,357	103,211	7,512,846
2019	3,009	105,919	122,008	8,453,451
2020	3,695	117,315	136,208	9,281,380
2021	5,170	123,706	151,241	10,014,228
2022	6,981	138,325	174,231	10,804,981
2023	7,310	162,387	207,578	11,655,182
2024	7,748	191,613	252,552	12,697,203

Notes: This table shows the registrations of fuel cell electric vehicles (FCEVs), battery electric vehicles (BEVs), plug-in hybrid electric vehicles (PHEVs), and hybrid electric vehicles (HEVs). The registration data is as of the end of March of each year and exclusively pertains to passenger vehicles.

Similarly, the HFCS aimed for 160 HCSs by 2020, 320 by 2025, and 900 by 2030. Figure 1 illustrates the trend in HCS deployments in Japan from 2014 to 2021, highlighting that although HCSs were constructed annually, the cumulative number of HCSs only reached 157 nationwide by 2021. Although this figure is nearly on par with the 2020 target, the number of HCSs must double by 2025 and increase six-fold by 2030 to meet future goals.

[4] The HFCS targeted 100 registrations by 2020 and 1,200 by 2030 for fuel cell buses. Similarly, it aimed for 500 registrations by 2020 and 10,000 by 2030 for fuel cell forklifts (Ministry of Economy, Trade and Industry, 2019).

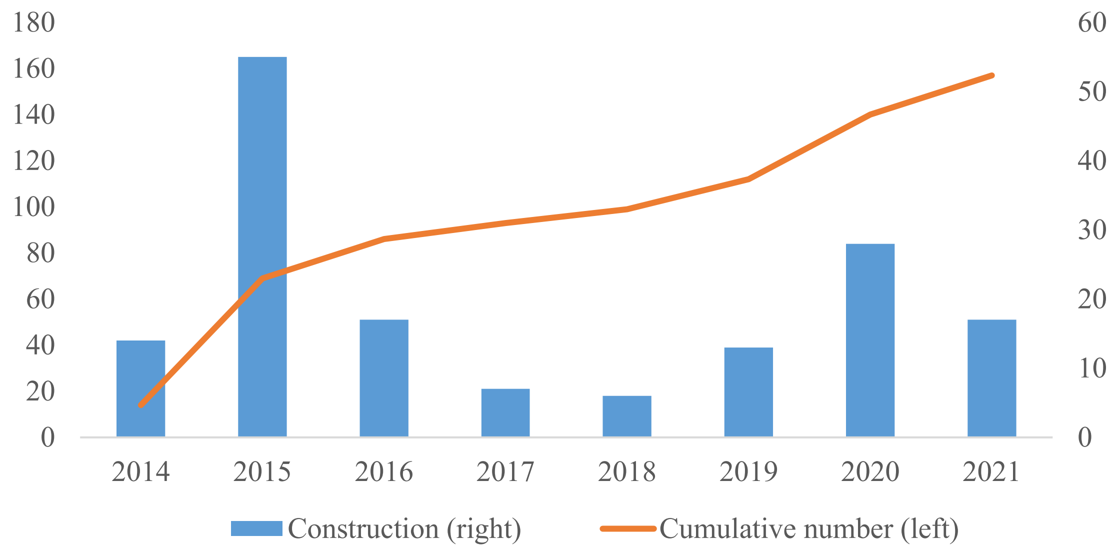

Fig. 1. Trends in HCS deployments in Japan

Notes: The bars represent the total HCS construction in each year. The line denotes the cumulative number of HCSs nationwide.

3. Data and sample

3.1. Data sources

We obtained administrative data on passenger vehicle registrations as of the end of March 2021 from the Automobile Inspection & Registration Information Association. Under the Road Transport Vehicle Act, all Japanese citizens must register their motor vehicles in the national vehicle registration system. Our analyses focused on 35 prefectures with at least one HCS as of March 2021, accounting for 88% of the total passenger vehicle registrations in Japan.[5] The dataset includes details on first registration years, carmakers, vehicle weight, fuel type, and owner's residential municipality. It covers 135 carmakers, including both domestic and foreign manufacturers, and six fuel types: gasoline, diesel, hybrid (including both gasoline- and diesel-electric), electric, hydrogen, and others (e.g., liquefied petroleum gas). Utilizing this fuel type information, we constructed a binary

[5] The selected 35 prefectures include Hokkaido, Miyagi, Fukushima, Ibaraki, Tochigi, Gunma, Saitama, Chiba, Tokyo, Kanagawa, Yamanashi, Niigata, Toyama, Nagano, Fukui, Gifu, Shizuoka, Aichi, Mie, Shiga, Kyoto, Osaka, Nara, Wakayama, Hyogo, Okayama, Hiroshima, Yamaguchi, Tokushima, Kagawa, Fukuoka, Saga, Kumamoto, Oita, and Kagoshima.

outcome variable that takes a value of one if the registered vehicle is hydrogen-powered.

We limited our sample to "standard" passenger vehicles first registered between 2013 and 2020. In Japan, passenger vehicles are classified into "small" and "standard,"[6] with FCEVs (Toyota Mirai and Honda Clarity) falling under the standard category. We excluded small passenger vehicles, as well as registrations from 2021, which only cover three months (January–March). Pre-2013 registrations were also omitted, as no FCEVs existed before the introduction of the Toyota Mirai in Japan in December 2014. However, we retained 2013 data to ensure at least one pretreatment period for our estimation technique. The final dataset comprises 9,973,652 registered passenger vehicles.

Data on HCSs were sourced from the Next Generation Vehicle Promotion Center and included details on station location, supply methods, capacities, business operators, operating days and hours, and opening dates. Between October 2014 and December 2020, 136 HCSs were established across 118 municipalities:105 municipalities had one HCS, nine had two HCSs, three had three HCSs, and one municipality had four HCSs.

We supplemented this with municipality-level data from various sources:

- System of Social and Demographic Statistics (Ministry of Internal Affairs and Communications): Population density, per capita income, fiscal soundness of municipal governments, share of individuals aged 15–65 years, share of university and postgraduate degree holders, share of workers in service sectors, and share of designated residential areas.

[6] A passenger vehicle is labelled small if its body length is below 4.7 meters, its width is below 1.7 meters, and its height is below 2.0 meters. If any of these conditions are not met, the vehicle is categorized as standard.

- Land General Information System (Ministry of Land, Infrastructure, Transport and Tourism [MLITT]): Residential land prices per square meter.
- National Land Numerical Information dataset (MLITT): Total number of gasoline stations per municipality in 2015.
- New Energy and Industrial Technology Development Organization (for 2014): Prefectural and municipal government incentives for promoting FCEV and HCS deployment.

3.2. Sample selection

During the sample period, 118 municipalities had at least one HCS, while 1,437 did not. As presented in Panel A of Table 2, municipalities with HCS exhibited higher population density, income, education levels, and local government support than those without HCS. Given these significant disparities, directly comparing municipalities with and without HCS could lead to biased estimates. To mitigate this issue, we employed propensity score matching to balance observable characteristics and isolate the effect of HCS deployment.

Following Nishitateno and Burke (2024), we selected the estimation sample using the following steps. First, we employed a logit model to estimate the propensity score of being "treated" for all available municipalities based on the variables listed in Table 2 during the pre-HCS deployment period. The years of the variables differ depending on data availability (see notes for Table 2).[7] Second, we constructed a sample using single nearest-neighbor matching within a caliper width of 0.2 of the propensity score without replacement.[8] We imposed a common support condition to satisfy the overlap

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[7] The years were also selected to ensure they reflect conditions before the establishment of HCS, maintaining the validity of the matching process.

[8] We selected a caliper width of 0.2, following Wang et al. (2013), who demonstrated that this value—calculated as 0.2 of the pooled standard deviation of the logit of the propensity score—

assumption, dropping HCS municipalities with a propensity score higher than the maximum or lower than the minimum among non-HCS municipalities. Panel B of Table 2 illustrates that this matching approach resulted in well-equalized means of the municipality variables during the pre-HCS deployment period between municipalities with and without an HCS. Additionally, Figure 2 confirms that the distribution of the propensity scores is well-balanced. We applied this matched sample (232 municipalities) throughout our analyses.[9] This final matched sample formed the basis of our empirical analysis, allowing us to assess the impact of HCS deployment while minimizing selection bias.

Table 2
Averages across municipalities during the pre-HCS deployment period

	A. Before matching			B. After matching		
	With HCSs	Without HCSs	Diff.	With HCSs	Without HCSs	Diff.
Population density	50	19	31***	50	61	–11*
Per capita income, thousand yen	3,444	2,837	606***	3,400	3,380	20
Residential land prices per square meter, thousand yen	167	48	119***	157	157	0
Share of people aged 15-65	0.65	0.60	0.05***	0.65	0.65	0
Share of university and postgraduate degree holders	0.16	0.1	0.06***	0.16	0.16	0
Share of workers in service sectors	0.68	0.61	0.07***	0.68	0.70	–0.02
Share of designated areas for residence	0.37	0.27	0.10***	0.37	0.38	–0.01
Number of petrol stations	33	12	21***	32	28	4
Fiscal soundness of municipal government	0.88	0.57	0.31***	0.88	0.92	–0.04
Prefectural government supports	0.76	0.64	0.12***	0.76	0.77	–0.01
Municipal government supports	0.18	0.03	0.15***	0.17	0.18	–0.01
Propensity score	0.28	0.06	0.22***	0.29	0.28	0.01
Number of municipalities	118	1437		116	116	

Notes: This table reports the results of balancing tests before and after matching. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. We used 4-year averages from 2010–2013 for population density, per capita income, residential land prices per square meter, the share of designated areas for residence, and fiscal soundness of municipal governments. The share of people aged 15–65 years, university and postgraduate degree holders, and workers in service sectors were averaged for 2010 due to data limitations. Prefectural and municipal government support and the number of petrol stations were averaged for 2014 and 2015, respectively.

optimizes the estimation of treatment effects.

[9] The only exception occurs when analyzing the potential spatial spillover effects of HCS deployment using a sample of non-HCS municipalities (Panel C of Table 4).

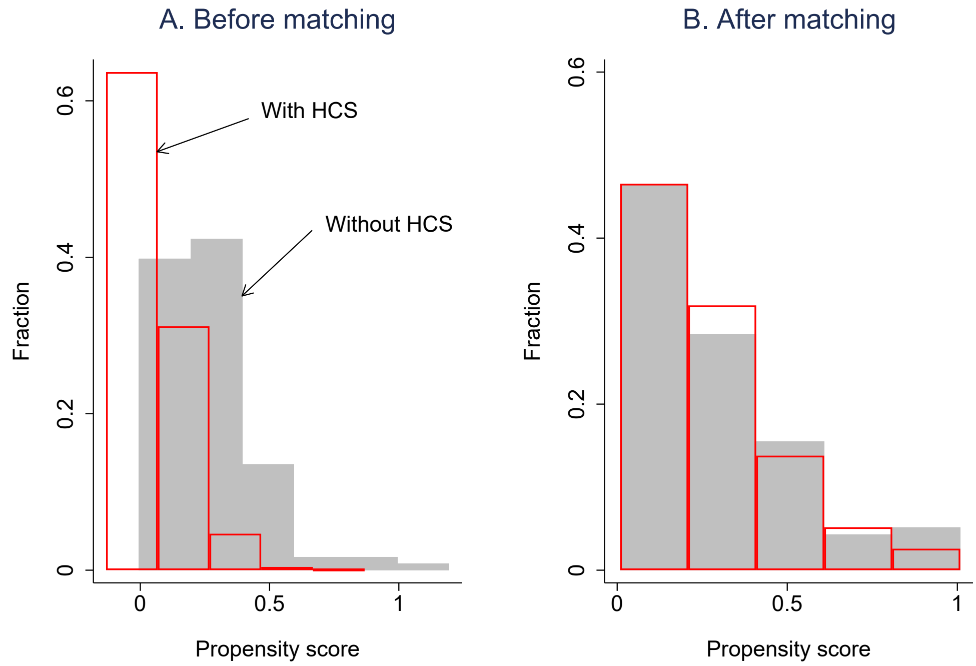


Fig. 2. Distribution of propensity score

Notes: The histograms illustrate the distribution of propensity scores for municipalities with and without HCSs before and after matching. The number of municipalities with and without HCSs are 118 and 1437 in Panel A and 116 and 116 in Panel B, respectively.

4. Empirical approach

4.1. Effects of HCS deployment on FCEV adoption

We employed a DD approach with multiple periods and variations in treatment timing. The standard approach for estimating staggered DD effects is the two-way fixed effects (TWFE) regression, specified as follows:

$$FCEV_{i,m,t} = \alpha_m + \omega_t + D_{m,t}\beta + \varepsilon_{i,m,t} \qquad (1)$$

$$FCEV_{i,m,t} = \alpha_m + \omega_t + \sum_{r \neq -1} 1[t - G_m = r]\beta_r + \varepsilon_{i,m,t} \qquad (2)$$

where *i* represents vehicle registration, *m* denotes the municipality, and *t* signifies the year. *FCEV* is a dummy variable indicating whether the fuel type for a passenger vehicle first registered in municipality m during year t is hydrogen. α and ω represent municipality- and year-fixed effects, respectively. D is an indicator for whether an HCS was deployed in municipality m during year t. In the static TWFE specification (1), β can be interpreted as the overall effect of deploying HCSs on the probability of registering FCEVs across municipalities and years.

In the dynamic TWFE specification (2), G_m is the earliest year in which an HCS is deployed in municipality m, and r indicates the year relative to the initial deployment. For example, $r = 0$ represents the first post-treatment year. The summation runs over all possible values of r except $r = -1$, as the first pretreatment year is set as the reference period. $\beta_{r \geq 0}$ captures the dynamic effect of HCS deployment on FCEV adoption over time, indicating whether the impact increases, diminishes, or remains stable during post-treatment years.

A key estimation issue is that the TWFE regression coefficients in a staggered DD setup may reflect both comparisons between treated and not-yet or never-treated groups and those between already treated groups (Callaway and Sant'Anna, 2021; de Chaisemartin and d'Haultfoeuille, 2020; Goodman-Bacon, 2021). The latter can lead to significant drawbacks, such as coefficients having incorrect signs due to negative weighting problems, particularly when treatment effects are heterogeneous across cohorts. In our setting, this is likely because HCSs are generally deployed based on expected returns, with additional stations being more likely in early-treated municipalities.

To examine the extent to which the treated groups receive negative weights in our data, we conducted a diagnosis for TWFE, as proposed by Jakiela (2021). We calculated

$\widetilde{D}_{m,t}/\sum_{m,t}\widetilde{D}_{m,t}^{2}$ where $\widetilde{D}_{m,t}$ is the residual from a regression of the treatment indicator ($D_{m,t}$) on the municipality- and year-fixed effects (α_m, ω_t). Figure 3 illustrates the distribution of negative weights across the treated municipality-year observations. Negative weights are observed for early-treated municipalities in the later years of our sample, specifically for those with HCSs first deployed in 2014 or 2015, and during 2019 and 2020.

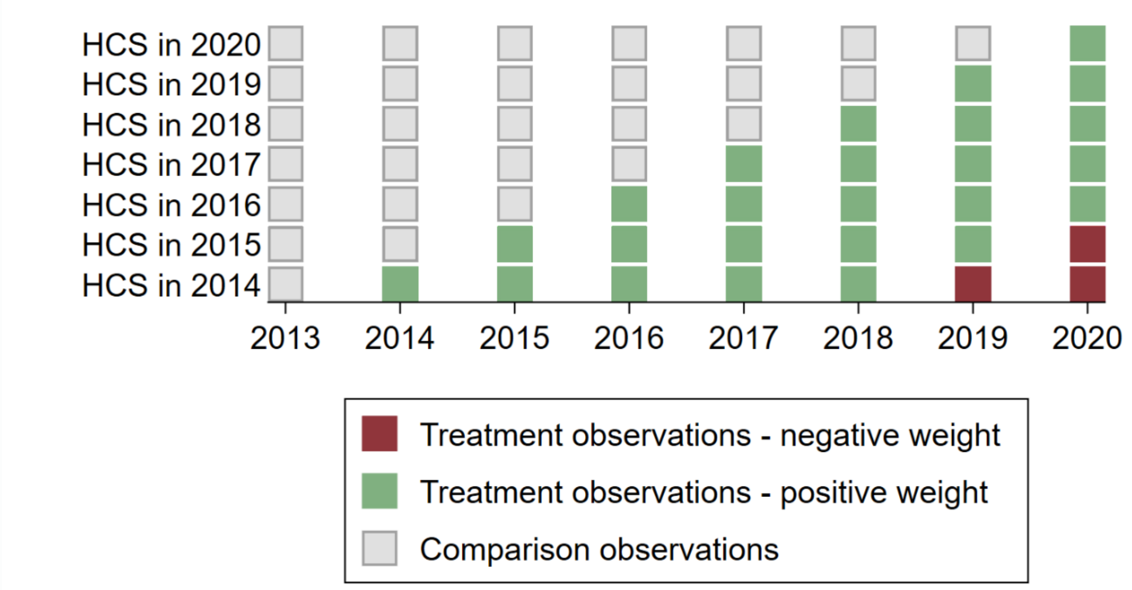


Fig. 3. Diagnosis for negative weights

Notes: This figure reports the distribution of weights across treated municipality-year observations. Weights are calculated based on Jakiela (2021). "HCSs in 2014" refers to municipalities where an HCS was first deployed in 2014.

To address these identification concerns, we applied Callaway and Sant'Anna's (2021) approach, which accounts for treatment heterogeneity. First, we estimated the average treatment effects for all group-years ($ATT(g,t)$) using a 2×2 DD estimation. This compares the expected change in FCEV adoption for the cohort treated in year g between years $g-1$ and t to that for never-treated cohort in year t

$$ATT(g,t) = \mathrm{E}\left[FCEV_{i,m,t} - FCEV_{i,m,g-1} | G_m = g\right] - \mathrm{E}\left[FCEV_{i,m,t} - FCEV_{i,m,g-1} | G_m = g'\right], \qquad \text{for any } g' > \mathrm{t} \qquad (3)$$

The reference period was the year before HCS deployment. For example, for the cohort where the first HCS was deployed in 2016, the reference period was 2015. This yielded two 2×2 DD estimates for pre-HCS deployment (2013–2015 and 2014–2015) and five for post-HCS deployment (2015–2016, 2015–2017, 2015–2018, 2015–2019, and 2015–2020), resulting in 49 2×2 DD estimates across seven treated cohorts.

Next, we aggregated these estimates using (a) a simple weighted average, (b) cohort-specific averages, and (c) event-study estimates. We used each observation size as a weight, assigning greater weights to estimates with larger observation sizes. Cohort-specific and event-study estimates help us understand how HCS deployment effects vary across cohorts and evolve.

The use of repeated cross-sectional data raises concerns about serial correlation in model errors over time and spatial correlation among municipalities within the same prefecture due to common shocks, such as prefectural government policies (Nishitateno and Burke, 2021). Failing to account for within-cluster correlations may lead to underestimated standard errors. To address this issue, we clustered the standard errors at the prefecture level throughout the analyses.

4.2. Effect of FCEV stock on HCS deployment

We quantified the link between FCEV stocks and HCS deployment using the following dynamic panel model:

$$HCS_{m,t} = \omega_m + \varphi_t + \beta_1 FCEVS_{m,t} + \beta_2 HCS_{m,t-1} + \boldsymbol{\gamma X_{m,t}} + \varepsilon_{m,t} \qquad (4)$$

where *m* denotes the municipality, *t* represents the year, *HCS* signifies the number of HCS deployed, $FCEVS$ is the accumulated FCEV registrations, and $\boldsymbol{X}$ is a vector of confounding factors, including population density, per capita income, fiscal soundness of municipal governments, and residential land prices. ω and φ are municipality- and year-fixed effects, respectively, while ε is the error term. We report standard errors clustered by prefecture.

Estimating Eq. (4) poses several challenges, including that municipality-fixed effects (ω) does not eliminate dynamic panel bias because the lagged HCS and ε may be correlated (Roodman, 2009). Additionally, $FCEVS$ may be endogenous if local subsidy policies influence both FCEV adoption and HCS deployment.

To address these issues, we apply the system GMM estimator to Eq. (4). The system GMM uses lagged differences and levels of the dependent variable as instrumental variables in a dual-equation system, offering superior efficiency compared to the difference GMM estimator (Blundell and Bond, 1998). We assume that changes in instruments are uncorrelated with fixed effects (Roodman, 2009). In our one-step system GMM estimation, the t-1 lagged HCS is considered predetermined but not strictly exogenous, whereas $FCEVS$ and $\boldsymbol{X}$ are treated as endogenous. Thus, we included every regressor in Eq. (4) in the instrument matrix, excluding municipality- and year-fixed effects.[10] The matrix was collapsed to limit the number of instruments, resulting in 282 instruments. We applied the forward orthogonal deviation transform, which subtracts the average of all available future observations from previous observations (Arellano and Bover, 1995).

[10] The Hansen-J test fails to reject the null hypothesis that the instruments are uncorrelated with the error term, and correctly excluded from the estimated equation.

5. Results

5.1. Estimated effects of HCS deployment on FCEV adoption

Table 3 presents the estimation results for Eq. (1) using the matched sample for repeated cross-sectional data on vehicle registrations from 2013 to 2020 and adopting Callaway and Sant'Anna's (2021) approach. Further, it reveals several important findings. First, the effect of HCS deployment on FCEV adoption is positive and statistically significant. The simple weighted average of the treatment effects for all treated municipalities is 0.0009, significant at the 5% level, with a 95% confidence interval ranging from 0.0002 to 0.0017 (Panel A of Column 1). This suggests that HCS deployment increased the probability of FCEV adoption by 0.09 percentage points during the post-HCS deployment period inside municipalities with HCSs relative to those without HCSs. Given that the mean probability of FCEV adoption after HCS deployment in HCS municipalities was 0.15, approximately 60% ($\approx$(0.09/0.15)$\times$100) of the increased FCEV adoption during the post-HCS deployment period can be attributed to HCS deployment.

Second, the effect of HCS deployment on FCEV adoption for multi-HCS municipalities is approximately 30% greater than that for single-HCS municipalities (see Panel A of Columns 2 and 3). The treatment timing for multi-HCS municipalities was set as the first year of HCS deployment (2015, 2016, or 2020). These results reflect the effectiveness of expanding HCS networks in promoting FCEV adoption.

Third, treatment effects differ across cohorts. The results suggest that HCS deployment increased the probability of adopting FCEVs by 0.07–0.12 percentage points in municipalities with HCSs first deployed in 2014 or 2015, whereas such effects were not observed for late-treated municipalities, except for the cohort in 2018 (Panel B of Column

1). This is consistent with early-treated municipalities being more likely to deploy additional HCSs—half (six out of 12) of the multi-HCS municipalities in our sample deployed their first HCSs in 2015.

Table 3
Effects of HCS deployment on FCEV adoption

	All	Single-HCS	Multi-HCS
	(1)	(2)	(3)
A. Simple weighted average	0.00093**	0.00083*	0.00116***
	(0.00038)	(0.00043)	(0.00034)
B. Heterogeneous effect across cohorts			
Cohort 2014	0.00075***	0.00075***	
	(0.00018)	(0.00018)	
Cohort 2015	0.00117***	0.00093***	0.00166***
	(0.00024)	(0.00017)	(0.00047)
Cohort 2016	0.00001	–0.00017**	0.00085**
	(0.00009)	(0.00009)	(0.00038)
Cohort 2017	0.00033	0.00033	
	(0.00021)	(0.00021)	
Cohort 2018	0.00060**	0.00060**	
	(0.00023)	(0.00023)	
Cohort 2019	0.00090	0.00090	
	(0.00061)	(0.00061)	
Cohort 2020	0.00933	0.01020	–0.00049
	(0.00771)	(0.00807)	(0.00035)
Average across cohorts	0.00203	0.00214	0.00082***
	(0.00131)	(0.00144)	(0.00026)
C. Event-study estimates			
Pre-HCS deployment average	0.00019	0.00019	0.00019
	(0.00018)	(0.00018)	(0.00018)
Post-HCS deployment average	0.00070**	0.00058**	0.00113***
	(0.00027)	(0.00029)	(0.00033)
Observations	4,282,178	4,033,958	3,202,000

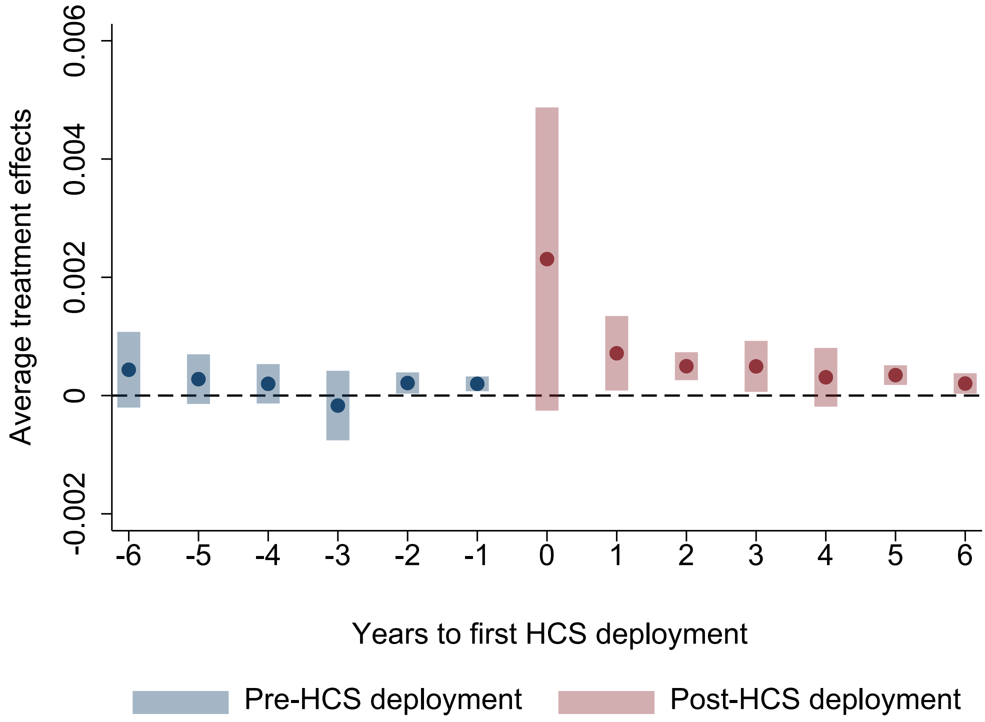
Notes: This table presents the estimation results for Eq. (1) using the matched sample for repeated cross-section data on vehicle registrations from 2013 to 2020 and adopting Callaway and Sant'Anna's (2021) approach. Column 1 reports the specification including all municipalities in the treatment group. Columns 2 and 3 restrict the treatment group to single- and multi-HCS municipalities, respectively, while maintaining the control group constant. Note that the treatment timing for multi-HCS municipalities was set as the first years of HCS deployment (either 2015, 2016, or 2020). Standard errors are robust to heteroscedasticity and clustered at the prefecture level.
***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Fourth, the dynamics of FCEV adoption were approximately parallel before HCS deployment, with no significant evidence of pre-HCS deployment effects, increasing confidence that the parallel trends assumption is met (Panel C). By contrast, FCEV adoption rates diverged between municipalities with and without HCSs during the post-HCS deployment period, with average treatment effects of 0.0007 for all treated municipalities, 0.0006 for single-HCS, and 0.0011 for multi-HCS municipalities.

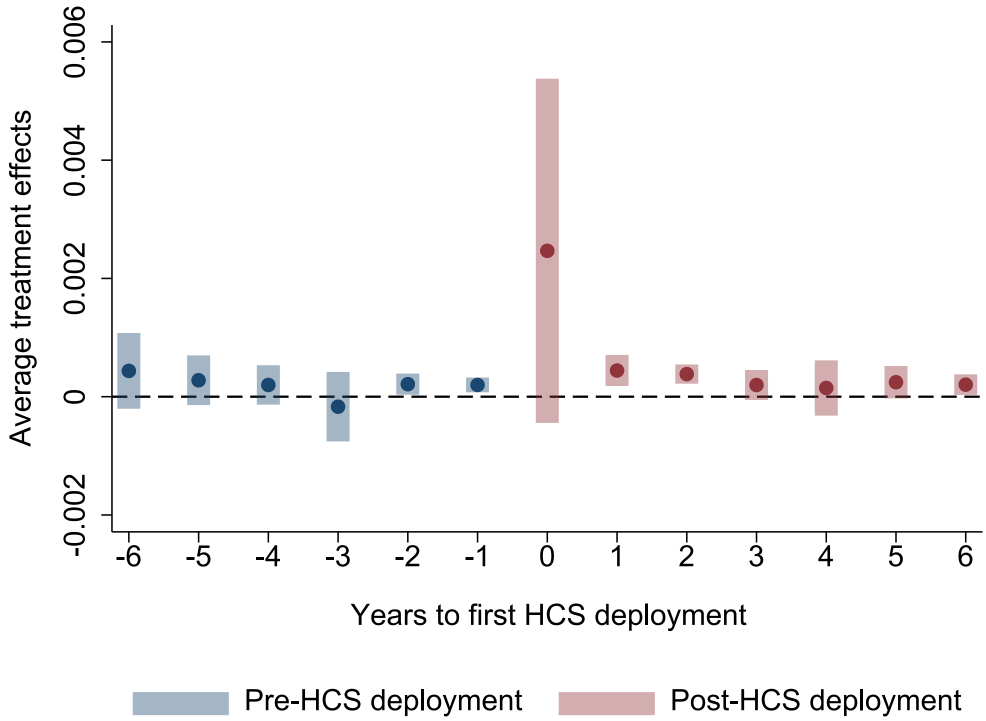
Figure 4 displays event-study estimates for Eq. (2) using the same matched sample and Callaway and Sant'Anna's (2021) approach. Panel A demonstrates that the effect was large in the initial period of HCS deployment; however, it diminished over time. The estimates suggest that HCS deployment increased the probability of FCEV adoption by 0.23 percentage points during the same year of deployment, whereas this effect was reduced to 0.02 percentage points after six years. A similar pattern is observed for single-HCS municipalities (Panel B). In the case of multi-HCS municipalities, the treatment effects appear to be relatively persistent but eventually diminish over time (Panel C).

The notable effect during the initial phase of HCS deployment may be attributed to prefectural or municipal governments proactively purchasing FCEVs as official vehicles to promote hydrogen mobility and raise public awareness. For example, municipalities like Tokyo-Setagaya acquired FCEVs in the same year as HCS deployment. However, the diminishing effects suggest that HCS deployment alone was insufficient to expand the early adopter base in FCEV markets.

Panel A. All treated municipalities



Panel B. Single-HCS municipalities



Panel C. Multi-HCS municipalities

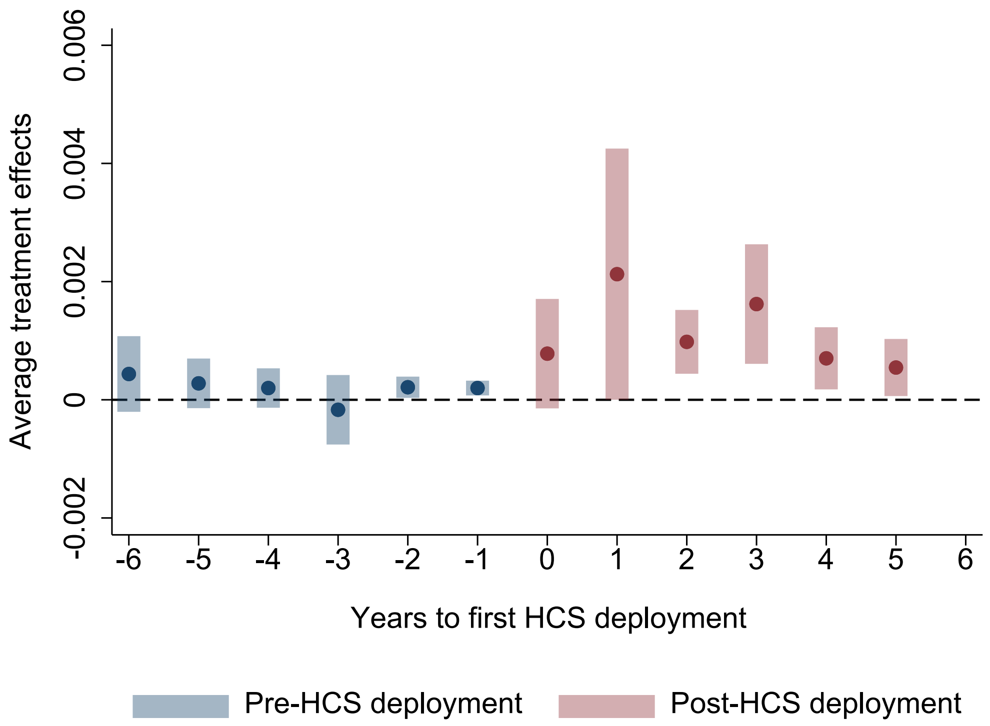


Fig. 4. Dynamic effect of HCS deployment on FCEV adoption

Notes: The figures present the event-study estimation results for Eq. (2) using the matched sample for repeated cross-sectional data on vehicle registrations from 2013 to 2020 and Callaway and Sant'Anna's (2021) approach. Panel A includes all the municipalities in the treatment group. Panels B and C restrict the treatment group to single- and multi-HCS municipalities, respectively, while maintaining the control group constant. Standard errors are robust to heteroscedasticity and clustered at the prefecture level. The circles show the point estimates of the average treatment effects, and the vertical bands represent the 95% confidence intervals.

5.2. Additional estimates

Table 4 presents the estimation results for the simple weighted averages obtained using alternative approaches, outcome variables, and treatments. In Panel A, the first row employs the standard TWFE specification instead of Callaway and Sant'Anna's (2021) approach to examine the extent to which the TWFE estimate deviates from our baseline estimate. We find that the TWFE estimate is approximately 40% larger than the baseline estimate.

The second and third rows in Panel A examine the validity of the parallel trend assumption in our setup. First, we incorporated covariates, including population density, per capita income, the fiscal soundness of the local government, and residential land prices at the municipality level, and implemented a doubly robust DD estimator based on inverse probability weighting and ordinary least squares (Callaway and Sant'Anna, 2021). Second, we used both never-treated and not-yet-treated municipalities as the control group rather than just never-treated municipalities. Including not-yet-treated municipalities enhanced the comparability of the control group. The results indicate that our baseline estimate is robust to these two procedures, boosting confidence in the parallel trend assumption.

Table 4
Alternative approaches and outcome variables

	Coefficients	Standard errors
Our baseline estimate	0.00093**	0.00038
A. Alternative approaches		
TWFE	0.00151*	0.00080
With covariates	0.00066**	0.00030
Both never-treated and not-yet-treated municipalities	0.00090**	0.00037
Municipal clustering adjustment	0.00093**	0.00040
Panel specification	0.05282*	0.03194
B. Placebo tests		
Gasoline	0.00075	0.00328
Diesel	–0.00229	0.00303
Hybrid	0.00069	0.00080
Electric	0.00004	0.00062
C. Spatial spillover effects		
Neighboring municipalities without HCSs	0.00001	0.00073

Notes: This table presents the estimation results for simple weighted averages using alternative approaches, outcome variables, and treatments. In Panel A, "TWFE" employs the standard two-way fixed effects specification instead of Callaway and Sant'Anna's (2021) approach. "With covariates" incorporates covariates including population density, per capita income, fiscal soundness of local government, and residential land prices at the municipality level and implements a doubly robust DD estimator based on inverse probability weighting and ordinary least squares. "Both never-treated and not-yet-treated municipalities" expands the control group to include both never-treated and not-yet-treated municipalities rather than only never-treated ones. "Municipal clustering adjustment" clusters standard errors at the municipality level instead of the prefecture level. "Panel specification" uses the municipality-year panel data with 1,848 observations instead of the repeated cross-sectional data with 4,282,178 observations. In this specification, the outcome variable is the % share of FCEVs in total standard passenger vehicle registrations. In Panel B, we use alternative binary outcome variables with different vehicle fuels rather than hydrogen. In Panel C, the estimation results for Eq. (5) assess potential spatial spillovers of HCS deployment using a sample of non-HCS municipalities with 8,652,721 observations.
***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

The fourth row of Panel A displays the results with standard errors clustered at the municipality rather than the prefecture level. Our concern is that model errors exhibit serial correlation across municipalities and that the relatively small number of clusters (34) in our setup could bias the standard errors. Given that our sample includes 232 municipalities, the results confirm that clustering adjustments have little impact on the standard errors.

The fifth row of Panel A replaces the repeated cross-sectional data (4,282,178 observations) with municipality-year panel data (1,848 observations). In this specification, the outcome variable is the percentage share of FCEVs in total standard passenger vehicle registrations. The results indicate that HCS deployment increased the share of FCEVs by 0.05 percentage points, suggesting that approximately 40% (≈(0.05/0.13)×100) of the increase in FCEV adoption during the post-HCS deployment period can be attributed to HCS deployment. This large effect aligns with our baseline estimates.

Panel B of Table 4 reports the results from placebo tests using alternative binary outcome variables with vehicle fuels other than hydrogen. As expected, HCS deployment did not significantly affect new vehicle registrations for other fuel types, such as gasoline, diesel, hybrid, and electric, as these were not subject to the treatment.

Panel C of Table 4 reports the potential spatial spillover effects. If HCS deployment increases early FCEV adoption in neighboring municipalities without HCS, our method may underestimate its effect. To examine this, we estimate the following specification for a restricted sample of vehicle registrations in non-HCS municipalities with 8,652,721 observations:

$$FCEV_{i,m,t} = \alpha_m + \omega_t + Near_{m,t}\beta + \varepsilon_{i,m,t} \qquad (5)$$

where *Near* is a dummy variable that takes a value of one if a non-HCS municipality is located within 10 km of an HCS and zero otherwise.[11] In cases where multiple HCSs were deployed at different times, we selected the first deployment. The remaining elements are identical to those in Eq. (1), and we adopt Callaway and Sant'Anna's (2021) approach. The results show no evidence of spillover effects, reinforcing the validity of our baseline estimates and confirming that they are not biased due to violations of the stable unit treatment value assumption.

5.3. Estimated effects of FCEV stock on HCS deployment

Table 5 presents the estimation results for Eq. (4) using panel data from 232 municipalities for 2014–2020, totaling 1,617 observations. We excluded 2013 because of the inclusion of a one-year lagged dependent variable in the model. Applying the system GMM estimator, Column 1 reveals that the FCEV stock coefficient is 0.002, which is significant at the 5% level, with a 95% confidence interval ranging from 0.0001 to 0.004. This suggests that an increase of 500 FCEV stocks in a municipality leads to an additional HCS deployment in that municipality.

As the outcome variable (count of HCS deployment) is count data, which consists of many zero values—approximately 90% of observations—Columns 2–4 of Table 5 present results for count models, including the Poisson, negative binomial, and zero-inflated negative binomial models, using the maximum likelihood estimator. The negative binomial model addresses overdispersion, where the conditional variance exceeds the mean of the count-dependent variable. The zero-inflated negative binomial framework

[11] According to the Ministry of Economy, Trade and Industry (2019), the acceptable travel time for users to reach an HCS is approximately 10 min by car, equating to approximately 7 km, assuming an average driving speed of 40 km per hour.

accounts for excess zeros in the outcome variable using log per capita income in the logit analysis.[12] The results suggest that for every one-unit increase in FCEV stock, the expected count of HCS deployment increases by 0.6% (≈(exp (0.006)−1)×100). These empirical findings highlight the role of indirect network effects in shaping market dynamics, providing a foundation for the policy consideration discussed in Section 5.4.

Table 5
Effects of FCEV stock on HCS deployment

Dependent variable: Count of HCS deployment				
	System GMM	Poisson	Negative binomial	Zero-inflated negative binomial
	(1)	(2)	(3)	(4)
FCEV stock	0.002**	0.006*	0.006*	0.006*
	(0.001)	(0.003)	(0.003)	(0.003)
Ln population density	–1.184*	–8.311	–8.310	–8.307
	(0.698)	(6.283)	(6.281)	(6.281)
Ln per capita income	1.024	11.873*	11.873*	11.872*
	(0.900)	(6.580)	(6.579)	(6.579)
Fiscal soundness of municipal government	–0.933*	–5.111***	–5.111***	–5.108***
	(0.481)	(1.389)	(1.388)	(1.388)
Ln land prices per km^2	0.069	–0.715	–0.715	–0.715
	(0.083)	(0.676)	(0.676)	(0.676)
1-year lagged HCS deployment count	–0.016	–1.936***	–1.936***	–1.936***
	(0.059)	(0.626)	(0.626)	(0.626)
Year-fixed effects	Yes			
Municipality-fixed effects	Yes			
Observations	1,617			

Notes: This table presents the estimation results for Eq. (4) using the panel data covering 232 municipalities from 2014 to 2020. Standard errors are robust to heteroscedasticity and clustered at the prefecture level. Column 1 adopts the system GMM estimator. To account for the nature of count data for the dependent variable, Columns 2–4 estimate Poisson, negative binomial, and zero-inflated negative binomial models, adopting the maximum likelihood estimator.
***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

5.4. Policy implications

As elaborated above, indirect network effects exist in Japan's FCEV market in both directions: HCS deployment promotes FCEV adoption, and an increase in FCEV stock leads to HCS deployment. Using our estimates, we examined the extent to which FCEV

[12] The coefficient of the log per capita income is − 2.502 and is statistically significant at the 1% level, suggesting that the log odds of being an excess zero decreases by 0.025 for every additional increase in per capita income. In other words, municipalities with higher income levels are more likely to have HCS deployments.

adoption can increase if the government target of 900 HCSs is achieved—equivalent to six additional HCSs per treated municipality in our sample. To quantify this effect, we followed a five-step approach:

First, we multiplied our panel estimate (0.05282) from Table 4 by six to measure the extent to which infrastructure development increases the share of FCEV in total passenger vehicle registrations. Next, we added the estimates from the first step to the FCEV share as of December 2020 for the 116 treated municipalities. Third, maintaining the vehicle mix constant as of December 2020, we calculated the number of additional FCEVs resulting from infrastructure development in each treated municipality. Fourth, if the estimated increase in FCEV stock exceeded 500, we computed the corresponding effect on HCS deployment (if not, the process stops). If the threshold was met, positive feedback loops arose until the FCEV increase fell below this level. Finally, we aggregated the individual municipality-level outcomes.

The Appendix reports the results. An important finding is that the treatment effects of HCS deployment are too small to generate positive feedback loops. In no treated municipality does the increase in FCEV registrations exceed 500, preventing further HCS expansion. On average, six additional HCS deployments lead to only 64 more FCEV registrations, with total additional registrations reaching 7,455. The largest increases occur in Tokyo-Setagaya (231), followed by Toyota (219), Okazaki (166), Oita (150), and Takasaki (148). Our preliminary calculation suggests that each HCS deployment results in 11 additional FCEV registrations, implying that each FCEV adoption through HCS deployment costs US$ 305,000—30 times more than direct FCEV purchase subsidies.

Several factors may explain the weak treatment effects of HCS deployment:

(a) High upfront costs—FCEVs are 35–47% more expensive than other electrified vehicles.

(b) High operating costs—although FCEV fuel costs are lower than those of gasoline vehicles, they remain higher than those of BEVs and HEVs. We calculated the fuel cost per kilometer for each vehicle, accounting for the fuel tank capacity, fuel price, and driving range. The results revealed that the fuel cost per kilometer for the Toyota Mirai was US$ 0.05, while that for the Nissan Leaf (BEV), Toyota Corolla Sport (HEV), and Toyota Corolla Sport (gasoline) was US$ 0.02, US$ 0.04, and US$ 0.07, respectively.

(c) Low public awareness—A survey conducted by the Next Generation Vehicle Promotion Center (2020) on the awareness of BEVs, PHEVs, and FCEVs among 413 households without electrified vehicles in Japan found that 62% of the households were unfamiliar with FCEVs, compared to 36% for BEVs and 48% for PHEVs.

(d) Insufficient incentives—Japan's support for early FCEV adopters is limited to subsidies and tax cuts to reduce purchasing costs, potentially weakening the HCS deployment effects. Khan et al. (2020) found that in addition to subsidies, free public transport, toll exemption, and free public parking are important determinants in deciding FCEV adoption for potential buyers.

6. Conclusion

The Paris Agreement, adopted in December 2015 at the 21st session of the Conference of the Parties to the United Nations Framework Convention on Climate Change, commits to limiting global warming to well below 1.5 degrees Celsius above pre-industrial levels. All participating countries are required to set greenhouse gas reduction and control targets from 2020 onwards and implement long-term plans. Given that road transport is a key source of greenhouse gas emissions, decarbonizing road transport has become an important policy issue across countries. The electrification of road transport through the diffusion of zero-emission vehicles is considered a promising pathway.

A critical feature of zero-emission vehicle markets is indirect network effects, where vehicle adoption depends on refueling infrastructure and vice versa. This study provides the first empirical evidence of these effects in Japan's FCEV market. We found positive and statistically significant indirect network effects on both sides of the market; however, these effects were too small to generate self-sustaining positive feedback loops. Our findings indicate that developing HCS networks at an early stage is prohibitively expensive and financially unsustainable, highlighting the limitations of early-stage hydrogen infrastructure development without strong demand-side growth.

Our study informs the necessity of fundamental reforms in hydrogen mobility strategies. Greater emphasis should be placed on demand-side measures such as reducing upfront and operating costs for FCEV adoption, increasing public awareness, and offering additional incentives. For example, subsidies to equalize upfront and operating costs between FCEVs and BEVs warrant consideration. Additionally, adopting FCEVs as official vehicles for national, prefectural, and municipal governments could enhance public awareness.

This study focuses exclusively on passenger cars because of data limitations. However, fuel cell technology is well-suited for long-haul trucking and bus operations, given its high energy density, rapid refueling time, and long driving range. Future research should explore indirect network effects in these applications to inform more effective hydrogen infrastructure policies. Examining FCEV markets in other countries, such as the United States, South Korea, and China, also represents an important direction for future studies.

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Appendix: FCEV registrations in treated municipalities in our sample

	Treated municipality	Share of FCEVs in total passenger vehicle registrations (%)		FCEV registrations		
		As of December 2020	After six HCSs are deployed	As of December 2020	After six HCSs are deployed	Diff.
1	Tokyo-Setagaya	0.07	0.39	54	285	231
2	Toyota	0.30	0.62	207	426	219
3	Okazaki	0.09	0.41	48	214	166
4	Oita	0.02	0.34	9	159	150
5	Takasaki	0.01	0.33	5	153	148
6	Toyama	0.04	0.36	18	163	145
7	Tokyo-Nerima	0.13	0.44	58	203	145
8	Toyohashi	0.07	0.39	33	175	142
9	Hachioji	0.07	0.39	33	175	142
10	Tokyo-Ota	0.14	0.46	62	201	139
11	Tokyo-Edogawa	0.04	0.36	17	143	126
12	Takamatsu	0.03	0.34	11	137	126
13	Yokkaichi	0.03	0.35	13	136	123
14	Iwaki	0.14	0.46	56	178	122
15	Kasugai	0.05	0.37	19	140	121
16	Koriyama	0.04	0.36	16	131	115
17	Fujisawa	0.04	0.35	13	125	112
18	Nagoya-Midori	0.09	0.40	29	136	107
19	Wakayama	0.05	0.36	15	120	105
20	Tokyo-Suginami	0.13	0.45	44	149	105
21	Toyonaka	0.02	0.34	7	110	103
22	Otsu	0.02	0.34	7	109	102
23	Matsudo	0.01	0.33	3	104	101
24	Tsu	0.04	0.35	12	113	101
25	Hirakata	0.02	0.34	7	102	95
26	Tsukuba	0.03	0.34	8	102	94
27	Tokyo-Koto	0.21	0.52	60	152	92
28	Kurume	0.03	0.34	8	99	91
29	Fukushima	0.02	0.34	7	97	90
30	Fukuoka-Higashi	0	0.32	1	91	90
31	Tokyo-Itabashi	0.10	0.41	27	115	88
32	Yokohama-Kita	0.05	0.37	15	101	86
33	Fukuoka-Hakata	0.10	0.42	27	112	85
34	Koshigaya	0.02	0.33	4	88	84
35	Yokohama-Tsuzuki	0.06	0.37	15	99	84
36	Nagoya-Nakagawa	0.10	0.42	27	110	83
37	Anjo	0.12	0.44	32	114	82
38	Tokorozawa	0.05	0.36	12	91	79
39	Tokushima	0.05	0.37	12	89	77
40	Kariya	0.24	0.56	57	133	76
41	Hiroshima-Asaminami	0.01	0.33	2	77	75
42	Tokyo-Shinagawa	0.17	0.48	39	113	74
43	Ibaraki	0.01	0.33	3	73	70
44	Shizuoka-Suruga	0.07	0.39	15	83	68
45	Saga	0.07	0.39	15	82	67
46	Sagamihara-Chuo	0.07	0.39	15	81	66
47	Kofu	0.07	0.39	15	80	65
48	Sendai-Miyagino	0.06	0.38	12	76	64
49	Niigata-Chuo	0.04	0.36	8	70	62
50	Tokyo-Chuo	2.58	2.89	502	564	62
51	Kyoto-Fushimi	0.03	0.35	6	67	61
52	Sagamihara-Minami	0.04	0.35	7	66	59
53	Yokohama-Asahi	0.05	0.37	10	69	59
54	Higashihiroshima	0.02	0.34	4	62	58
55	Okayama-Minami	0.03	0.35	6	63	57
56	Fukuoka-Nishi	0.02	0.33	3	59	56
57	Sapporo-Toyohira	0	0.32	0	56	56
58	Tochigi	0	0.32	0	54	54
59	Kitakyushu-Kokurakita	0.05	0.36	8	62	54
60	Kasukabe	0.02	0.33	3	56	53

61	Kure	0.01	0.32	1	54	53
62	Nagoya-Minato	0.19	0.50	31	84	53
63	Hamamatsu-Higashi	0.04	0.35	6	58	52
64	Inazawa	0.05	0.37	8	58	50
65	Nisshin	0.12	0.44	18	65	47
66	Nagoya-Naka	0.44	0.76	65	112	47
67	Shunan	0.09	0.41	13	59	46
68	Chiba-Hanamikawa	0.01	0.33	2	47	45
69	Narita	0.06	0.37	8	53	45
70	Yokohama-Naka	0.19	0.50	26	70	44
71	Tokyo-Chiyoda	0.54	0.86	75	119	44
72	Chiba-Mihama	0.13	0.45	17	58	41
73	Kawasaki-Kawasaki	0.10	0.42	13	54	41
74	Saitama-Minuma	0.02	0.34	3	43	40
75	Yokohama-Izumi	0.05	0.36	6	46	40
76	Sayama	0.08	0.39	9	46	37
77	Nagoya-Higashi	0.20	0.51	22	58	36
78	Osaka-Chuo	0.09	0.41	10	45	35
79	Saitama-Midori	0.02	0.34	2	37	35
80	Toda	0.07	0.39	8	43	35
81	Tama	0.08	0.40	9	43	34
82	Yokohama-Minami	0.05	0.36	5	39	34
83	Ebina	0.10	0.42	11	45	34
84	Ama	0.06	0.37	6	39	33
85	Kitanagoya	0.04	0.36	4	36	32
86	Kyoto-Minami	0.08	0.40	8	40	32
87	Onojo	0.10	0.42	10	42	32
88	Miyoshi	0.21	0.53	21	53	32
89	Gotenba	0.02	0.34	2	34	32
90	Nagakute	0.06	0.38	6	36	30
91	Isehara	0.01	0.33	1	30	29
92	Tokyo-Arakawa	0.28	0.59	24	52	28
93	Osaka-Joto	0.02	0.34	2	29	27
94	Gamagori	0.02	0.34	2	29	27
95	Nagoya-Atsuta	0.25	0.57	21	47	26
96	Takayama	0.02	0.34	2	28	26
97	Saitama-Nishi	0.01	0.33	1	26	25
98	Muroran	0.05	0.37	4	28	24
99	Saitama-Sakura	0.13	0.44	9	32	23
100	Osaka-Suminoe	0.06	0.37	4	26	22
101	Tokoname	0.14	0.45	9	30	21
102	Toki	0.05	0.36	3	24	21
103	Kobe-Hyogo	0.05	0.37	3	22	19
104	Kitakyushu-Yahatahigashi	0.05	0.37	3	21	18
105	Koga	0.05	0.37	3	20	17
106	Ena	0.12	0.44	6	22	16
107	Shime	0.02	0.34	1	14	13
108	Sakai-Mihara	0.08	0.39	3	16	13
109	Ginan	0.03	0.34	1	13	12
110	Yoro	0.12	0.44	4	14	10
111	Oguchi	0.19	0.50	6	16	10
112	Miyawaka	0.09	0.40	2	9	7
113	Kugayama	0.05	0.37	1	7	6
114	Yaotsu	0.18	0.49	2	6	4
115	Itano	0.18	0.50	2	5	3
116	Tajiri	0	0.32	0	2	2
	Total	-	-	2,325	9,780	7,455

Note: This table shows the potential increase in FCEV registrations if six additional HCSs are deployed in each of the 116 treated municipalities of our sample.