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Spatially informed demand-side policies for green hydrogen diffusion in Europe

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Green hydrogen faces an implementation gap: demand substantially lags policy ambitions. Here, combining an installation-level model of green hydrogen demand with an original database of >14,000 potential offtakers in Europe, we show that, conditional on diffusion patterns mirroring natural gas power generation (a historical analogue), demand-side spatial considerations are critical for closing this gap. Spatial spillovers—where local adoption increases adoption likelihood nearby—strongly shape diffusion, and their effect rises (>20-fold) when green hydrogen is not cost competitive. Spillover potential is concentrated in Central–Western Europe and hard-to-abate sectors: over half of the 10% most central installations are located in five German or Belgian industrial regions. Spatially informed policies deliver superior outcomes: targeting the most central offtakers improves policy cost-effectiveness by up to 41% (€0.96 kg^{-1}) in a size, sector and cost-controlled setting and 15% (€0.20 kg^{-1}) when following the European Hydrogen Bank auction format.

Green hydrogen is widely regarded as a critical component of decarbonized energy systems[1,2]. Policymakers share this view: the European Union (EU) and 18 of its 27 member states have adopted green hydrogen strategies[1,3]. The EU plans to produce 10 Mt of green hydrogen domestically and import an additional 10 Mt per year by 2030[3], with the aim of covering 10% of its final energy demand by 2050[4]. To achieve these targets, substantial policy intervention may be required: by the end of 2023, less than 1% of EU hydrogen production originated from clean sources[5] and fewer than 7% of global capacity announcements had been completed on schedule[6].

This raises questions about how to best design green hydrogen policies. Most funding today comes from supply-side instruments designed to minimize subsidy needs, such as the European Hydrogen Bank (EHB) auctions (Supplementary Note 1 and Supplementary Table 1). This approach has shown deficiencies: its 2025 iteration resulted in only €270 million of allocations—20% of the available budget. Scholars[6] and practitioners[1] increasingly call for demand-side measures that go beyond existing portfolio standards for aviation[7], shipping[8] and industrial hydrogen[9]. These could be organized as place-based policies[10] such as the EU hydrogen valleys, which support regional value chains, or as industrial policies directed to specific sectors, such as the hard-to-abate chemicals and iron and steel industries[11].

The diffusion of green hydrogen demand at the European system level depends on the adoption decisions of thousands of individual offtakers that can switch from fossil-based energy sources to green hydrogen or its derivatives. These decisions depend on techno-economic factors, most importantly cost competitiveness relative to incumbent technologies as well as the presence of complementary infrastructure such as transmission, distribution and storage, reliable production routes and established markets and institutions for trade[12–14]. This creates interdependencies between supply, infrastructure and demand and among geographically proximate offtakers. These can lead to coordination failures[15,16] and reinforce technology lock-in[17] but also generate spatial spillovers: the presence of adopters increases the likelihood of further adoption nearby. In addition to shared infrastructure, spillovers may arise from the materialization of local supply chains and knowledge transfer[18,19]. Empirically, spatial spillovers have been observed for renewable generation[20,21], rooftop solar[22], heat pumps[23] and hydrogen-based steelmaking[24] (Supplementary Note 2). Yet, the structure of green hydrogen demand, and

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the complex demand-side interdependencies embodied by spatial spillovers, are only weakly represented in policies today. EHB auctions disregard demand. For EU hydrogen valleys, the link is weak: across all 22 valleys, targeted demand amounts to only 0.2 Mt (equivalent to 1% of the EU's 2030 target; Extended Data Fig. 1). Designation also does not account for diffusion processes over time or functional linkages within or beyond valleys, which often correspond to administrative units[25].

One reason for this under-representation is that models of green hydrogen demand rarely combine installation-level details with a systems perspective. European climate and energy policies strongly rely on scenarios derived from integrated assessment models (IAMs) and energy system models (ESMs), for example, the Price-Induced Market Equilibrium (PRIMES) model used in the Fit for 55 policy package[26–28]. By representing complex feedback loops between energy and other economic and environmental sectors, IAMs are well positioned to analyse system-level green hydrogen pathways but struggle to represent the sectoral detail and spatial resolution required for spatially informed policymaking[29]. ESMs offer the spatial, temporal and sectoral representation needed for infrastructure studies[30,31], yet most research does not capture spatial spillovers at the installation level. Granular techno-economic models may offer installation-level detail but focus on specific sectors or regions[32,33] or do not model diffusion processes[34]. Logistic diffusion models used to inform feasibility assessments for green hydrogen[35] are increasingly data driven and can capture locally differentiated conditions. However, as smooth single-technology models[14], they struggle to represent system linkages and can become unstable with noisy data[36].

Here we investigate how the spatial patterns of green hydrogen demand affect the evolution of Europe's prospective hydrogen economy and derive implications for spatially informed demand-side policies (Fig. 1). First, we build a bottom-up (installation-level) empirical model that links adoption to cost competitiveness and spatial spillovers, drawing on the historical diffusion of natural gas power plants as analogue for green hydrogen demand. Both share structural similarities, including physical and chemical properties, infrastructure requirements and spatial patterns, which produce diffusion processes shaped by spillovers from demand-infrastructure interdependencies, supply-chain materialization and knowledge exchange (Supplementary Note 3). We then examine where in Europe such spillovers are most likely to emerge. To that end, we conceptualize the European hydrogen economy as a network of 14,108 offtakers and use network centrality metrics—indicators of structural importance and influence—as markers for spillover potential, both locally (hydrogen valleys) and between regions (hydrogen corridors). Finally, we evaluate whether policies that deliberately target regions or sectors with high spillover potential can enhance the cost-effectiveness of demand-side interventions.

Our results indicate that spatially informed, demand-side policies are key for closing the green hydrogen implementation gap: spatial spillovers are a strong driver of diffusion that is most relevant (>20 times the average) if green hydrogen is costly. Spillover potential concentrates in a narrow set of industrial regions (for example, Antwerp/Flanders and the Rhine-Ruhr valley) and in hard-to-abate sectors (chemicals, metals and steel), indicating clear targets for place-based and industrial policy. Conditional on green hydrogen following natural gas power plant diffusion patterns, spatially informed policies raise average policy cost-effectiveness by up to 41% (€0.96 kg^{-1}) in a controlled setting and 15% (€0.20 kg^{-1}) under an EHB auction format.

Cost competitiveness and spatial spillovers in diffusion

We model adoption as a function of cost competitiveness, spatial spillovers and infrastructure access, using natural gas power plants as a historical analogue for green hydrogen demand[35,37]. The lack of reliable historical data makes modelling the diffusion of early-stage energy technologies challenging[14,36]. Green hydrogen demand today is confined to refining and chemicals, with <1% stemming from clean sources. Project announcements are overconfident[5,6]. We therefore turn to natural gas power plants as a historical analogue, following a structured screening process along the Systematic Historical Analogue Research for Decision-making framework (SHARD)[38], consistent with the approach for calibrating diffusion models for feasibility studies[37].

Natural gas power plants share structural similarities with green hydrogen, including physical and chemical properties, infrastructure requirements, market structure and some end uses[39] (Supplementary Note 3). Both, especially cogeneration plants, exhibit similar spatial patterns tracking industrial activity and population centres (Supplementary Figs. 1 and 2). Despite their heterogeneity, hydrogen end uses are similar in terms of complexity and customization needs[40], creating conditions for parallel spatial spillovers linked to shared infrastructure, supply-chain materialization and knowledge exchange across different components and subsystems[18,19,41]. Natural gas power generation also features some technological heterogeneity (steam, gas and combined-cycle turbines; Supplementary Fig. 3). Unlike renewable generation, natural gas receives limited policy support (€10 billion versus €83 billion for renewables in 2021, before the Ukraine war)[42], providing a cleaner baseline for policy evaluations.

We implement the empirical model using a logistic regression via a generalized estimating equations (GEE) procedure that accounts for autocorrelation over time (Methods), with adoption of natural gas power generation at observed plant sites (as of February 2026) as dependent variable. We treat cost competitiveness as the principal techno-economic driver of diffusion and define it as the euros per megawatt-hour differential between entrant and incumbent technologies (for example, the euros per megawatt-hour gap between e-kerosene and conventional kerosene in aviation). As pairwise levelized cost comparisons between natural gas and incumbent fuels, such as coal, rely on weak historical data and do not adequately capture competition[43], we measure cost competitiveness using an empirical proxy. We construct this proxy from the residuals of a first-pass regression that excludes direct cost terms, assuming that the remaining unexplained variation is dominated by cost competitiveness (Methods). In regional policy analyses, spatial spillover pressure has been represented as the intervention region's size (latent demand or capacity deployment) relative to the global market[44]. We transfer this metric to an installation level, by representing spatial spillover pressure by comparing local to global diffusion levels. We also include distance to natural gas transmission pipelines and navigable waterways as complementary measures of access to the physical distribution infrastructure required for natural gas or hydrogen delivery[45] (Extended Data Fig. 2). Robustness tests yield consistent results for using cogeneration and wind plants as analogues and do not suggest specification concerns (Supplementary Tables 2–5 and Supplementary Figs. 4–10).

Results (Extended Data Table 1) suggest that cost competitiveness and spatial spillovers are strongly and positively associated with the probability of adoption and interact with each other (as indicated by statistically significant interaction term). In other words, the change in adoption probability for a small change in cost competitiveness (marginal effect) depends on the level of spatial spillovers and vice versa. To compare effect sizes, we average this marginal effect and normalize it by the variables' standard deviation (s.d.) (Fig. 2a). Cost competitiveness has the largest influence (14.5 percentage points (pp) per s.d., 33% relative to average adoption probability), roughly eight times that of spatial spillovers (1.7 pp per s.d., 4%). Distance to waterways and natural gas transmission pipelines (not statistically significant) has negligible effects (below 0.3 pp, 0.6%), indicating that offtaker interdependencies matter more than physical geography. The marginal effect of cost competitiveness (Fig. 2b) peaks sharply around cost parity, where the cost gap between entrant and incumbent technology is narrow and increases once this threshold is crossed: across all different spatial spillover levels, it peaks between −€35 and €75 MWh^{-1}.

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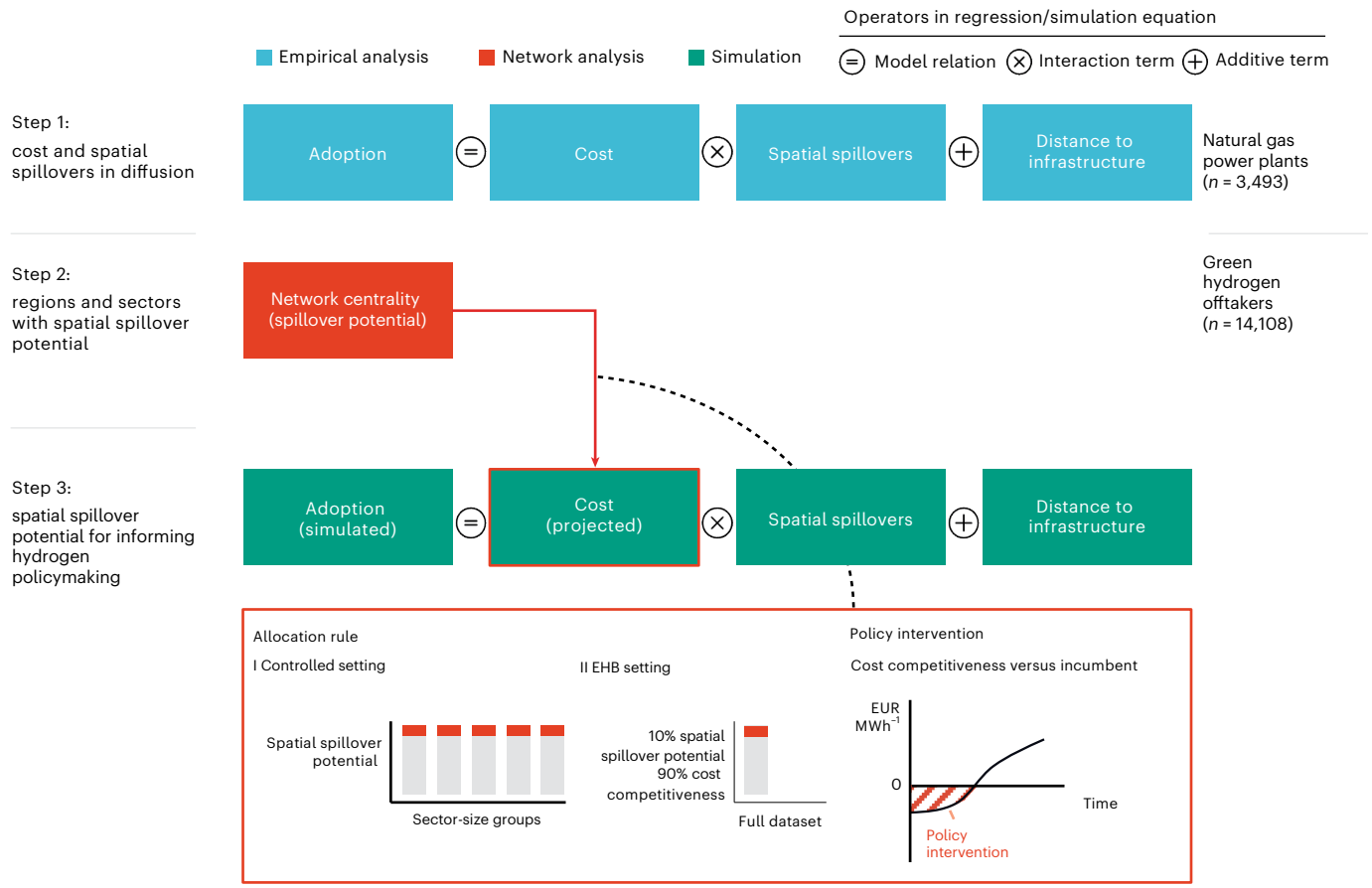

Fig. 1 | Illustration of methodological approach. The research methodology combines empirical, network and simulation analyses to evaluate the role of spatial patterns in Europe's prospective hydrogen economy and green-hydrogen policymaking. The analysis includes the development of an original dataset of 14,108 prospective green-hydrogen offtakers, which is used to quantify spatial spillover potential, calibrate diffusion dynamics and evaluate spatially targeted policy interventions.

Spatial spillovers (Fig. 2c) matter most when cost competitiveness is low (tenth percentile, −€210 MWh^{-1}) and local diffusion is high (>0.5). As cost competitiveness rises (above the 50th percentile), the peaks shift, indicating that spillovers activate at moderate diffusion levels (<−0.5) and, beyond the 75th percentile, become immaterial. Replacing the empirical cost proxy with external levelized cost of electricity (LCOE) measures[43] yields consistent results, increasing the relative importance of spillovers versus cost competitiveness (Supplementary Fig. 8).

Regions and sectors with spatial spillover potential

Next we examine how spatial spillovers may unfold in a prospective hydrogen economy. We identify potential offtakers by constructing an original database of 14,108 geo-located installations across EU countries, spanning industry, power and heating installations, airports, ports and fuel stations that could switch from fossil energy sources to green hydrogen. We exclude applications such as passenger vehicles and railways that are unlikely to see material hydrogen adoption, given the clear economic or technological superiority of alternatives[46]. In total, the database covers about 70% of EU emissions and all industrial installations emitting more than 25 kt CO_2 annually[47] (Methods).

We capture the demand-side interdependencies represented by spatial spillovers by conceptualizing the prospective hydrogen economy as a network, where nodes are offtakers and edges relational ties on the basis of spatial proximity. Network centrality is as a marker of spillover potential: it reflects the structural importance of a node within the network topology and thus how strongly offtakers influence others[48]. We use two complementary metrics: degree centrality, indicating hydrogen valleys (local spillovers via direct neighbours) and betweenness centrality, which quantifies the role of offtakers in mediating hydrogen corridors between otherwise disconnected regions (Methods).

Next, we analyse how spatial spillover potential, as measured by centrality metrics, is distributed across regions and sectors, pinpointing targets for place-based and industrial policy interventions. Degree centrality (Fig. 3a, hydrogen valleys) peaks along the North Sea coast and Rhine-Ruhr valley: half of the offtakers in the highest centrality decile are located in only 5 out of 243 regions in Belgium (Antwerp and East Flanders) and Germany (Düsseldorf, Cologne and Rheinhessen-Pfalz). This distribution mirrors European industrial geography[49], linking centrality to the footprint of hard-to-abate industries. Additional clusters in metropolitan areas (for example, Paris and Berlin) and coastal regions further tie centrality to population density and transport infrastructure. A closer look at North Rhine-Westphalia (Fig. 3c) shows that influential offtakers belong primarily to hard-to-abate industries and cluster in a 'hydrogen valley' within a 50-km radius between Düsseldorf and Dortmund. Betweenness centrality peaks (Fig. 3b, hydrogen corridors) run from the North Sea through Germany and Austria towards southeastern Europe, with additional signals in coastal Spain and Italy: half of the offtakers in the highest centrality deciles are located in 11 regions that, in addition to the aforementioned 5, include Lombardy and Emilia-Romagna (Italy), Münster and Arnsberg (Germany) and Hainaut and Western Flanders (Belgium). These corridors may be critical for enabling cross-regional diffusion: a view of Eastern Austria/Moravia (Fig. 3d) illustrates, for example, a link extending from Brno and Zlín (non-metallic mineral

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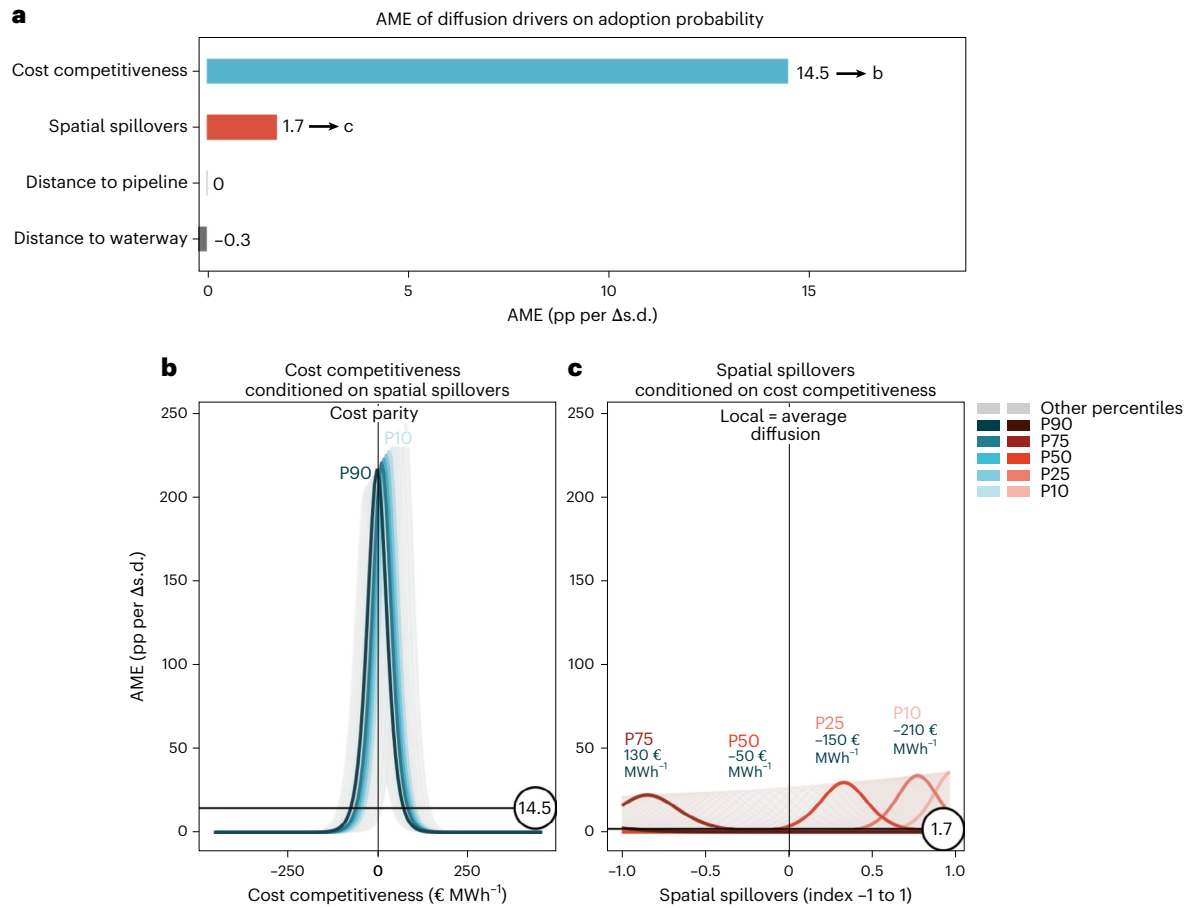

Fig. 2 | Average marginal effects of spatial spillovers and cost competitiveness on adoption probability. a, Average marginal effects of all explanatory variables. Cost competitiveness and spatial spillovers represent the primary drivers of technology diffusion, with cost competitiveness exhibiting a substantially larger average effect. **b**,**c**, Average marginal effects of cost competitiveness (**b**) and spatial spillovers (**c**) conditional on the respective interacting variable. Coloured lines represent marginal effects across the predictor range for selected percentiles of the conditioning variable; grey ribbons indicate the range across all values of the conditioning variable. Horizontal black lines indicate the overall average marginal effects, and vertical black lines indicate the reference points of cost parity and average spatial influence. Spatial spillovers exhibit the strongest effect near cost parity and under high local diffusion pressure. Average marginal effects are derived from the logistic regression model presented in Extended Data Table 1 using finite-difference approximations and standardized by the predictor s.d. Results are based on historical natural gas power plant adoption as an analogue for green hydrogen diffusion and include 3,493 power plant units. AME, average marginal effects.

plants) through the Vienna Basin to industrial centres (Leoben metallurgical cluster, Graz) in Austria's Styria region.

As place-based elements of its hydrogen policy portfolio, the EU designates hydrogen valleys and corridors. We show that, with few exceptions (Northern Italy), EU-designated valleys lie outside the areas with the strongest spatial spillover potential. While hydrogen valley designation follows an ecosystem approach in which demand represents one of several elements; this nevertheless reveals a disconnect between current place-based policy design and spillover potential, which is critical if these valleys are to catalyse demand for green hydrogen[25]. As part of the RePowerEU initiative[50], the EU has indicated three corridors for hydrogen imports (the North Sea, Mediterranean and Ukraine, operationalized as five subcorridors in the EU hydrogen backbone plan)[51]. While these are not inconsistent with observed patterns—the North Sea coast, for example, exhibits high spillover potential—these corridors are broad and could be refined through an explicit link to spillover potential.

Figure 4 shows the distribution of spatial spillover potential across sectors. In many hard-to-abate industries, degree centrality (hydrogen valleys) shows two peaks (bimodality) and extreme values are more common than in a typical distribution (heavy tails) (Fig. 4b). This points to a subset of offtakers with disproportionately high spillover potential: about one-quarter in chemicals and shipping and about one-fifth in non-ferrous metals fall into the top decile of centrality. Prominent installations in these peaks include the ThyssenKrupp steel plants in Duisburg and the INEOS and Evonik chemical sites in the Ruhr valley—all of which located in the hydrogen valley of North Rhine-Westphalia (Fig. 3c). For betweenness centrality (Fig. 4c, hydrogen corridors), extreme values are again most common in hard-to-abate sectors: in the chemicals and iron and steel sectors, 40% of offtakers fall into the top decile of centrality. These peaks include many of the same high-profile plants, such as the Duisburg steelworks, but also extend beyond Germany and the Benelux to sites such as Eni's Sannazaro refinery south of Milan. This pattern is notable, as the hard-to-abate industrial sectors with the strongest spikes are also viewed as priority targets for green hydrogen owing to a lack of alternative decarbonization technologies[11] and a comparably narrow cost differential versus fossil incumbents[6].

Spatial spillover potential for informing hydrogen policy

EHB auctions, the EU's flagship green hydrogen policy instrument, award funds to suppliers requiring the lowest subsidy per kilogramme of green hydrogen produced[52]. We argue that incorporating demand-side criteria targeting regions and sectors with high spillover

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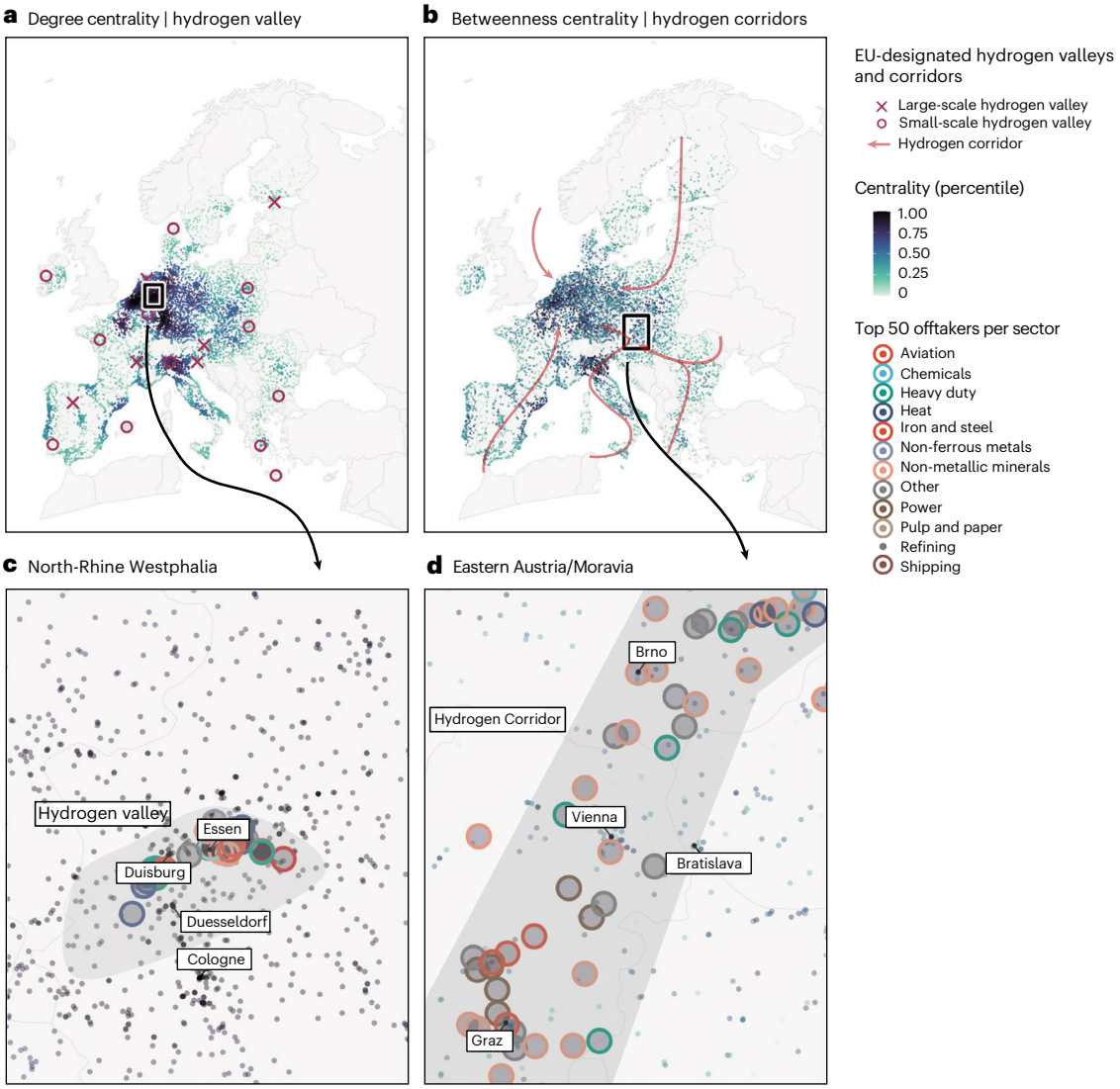

Fig. 3 | Spatial spillover potential of prospective green-hydrogen offtakers across regions. a,**b**, EU distribution of degree centrality (**a**) and betweenness centrality (**b**), representing local clustering potential and corridor potential, respectively. Markers indicate hydrogen valleys designated by the EU, distinguishing large-scale and small-scale valleys. Arrows indicate hydrogen import corridors defined by the European Hydrogen Backbone. High-centrality locations are concentrated in industrial regions and show limited alignment with existing policy-defined valleys and corridors. **c**,**d**, Regional examples illustrating local centrality distributions in North Rhine-Westphalia (**c**) and Eastern Austria/Moravia (**d**). The 50 offtakers with the highest centrality scores are highlighted, with sector categories indicated by point outlines. Remaining installations are shown using the same centrality-based colour scale as the European maps. Highly central installations form potential hydrogen valleys and corridors dominated by hard-to-abate industrial sectors. Metrics are calculated for 14,108 offtakers and standardized to a 0–1 scale. Basemap data from Natural Earth (https://www.naturalearthdata.com).

potential substantially improves the EHB's and other policies' effectiveness in achieving stated objectives by inducing adoption beyond targeted installations.

We evaluate this proposition in three steps. First, we project green hydrogen demand (excluding policies beyond carbon pricing) by computing each offtaker's demand as the product of hydrogen-specific energy use and its simulated adoption status (2024–2100; building on the empirical analysis presented above). Second, we use this as a baseline to assess a spatially informed demand-side intervention controlling for sector, cost and size. Third, we quantify the impact of adding a demand-side spatial spillover criterion to an EHB-style auction design (Methods). As our results are based on the empirical analysis, they are conditional on green hydrogen demand following a spatial diffusion process similar to natural gas power generation (Supplementary Note 2).

The analysis is subject to two main uncertainties: the cost competitiveness of green hydrogen relative to fossil incumbents and competition from alternative decarbonization technologies (electrification, carbon capture, utilization and storage (CCUS) or biomass), which are captured through sectoral saturation rates capping hydrogen diffusion. We vary both inputs using a three-by-three matrix. For cost competitiveness, we consider conservative, mean and progressive cost trajectories, reflecting ranges in the assumptions on cost, lifetime, capacity factor and efficiency of electrolysers, electricity cost and interest rates[6] (Supplementary Fig. 11 and Supplementary Table 5). For saturation rates (Extended Data Table 2, Supplementary Fig. 12 and Supplementary Tables 6–17), we include a restricted case (core applications such as refining, chemicals and iron and steel), a central case (adding high temperature industrial processes and selected transport uses) and an extended case (including applications where alternatives

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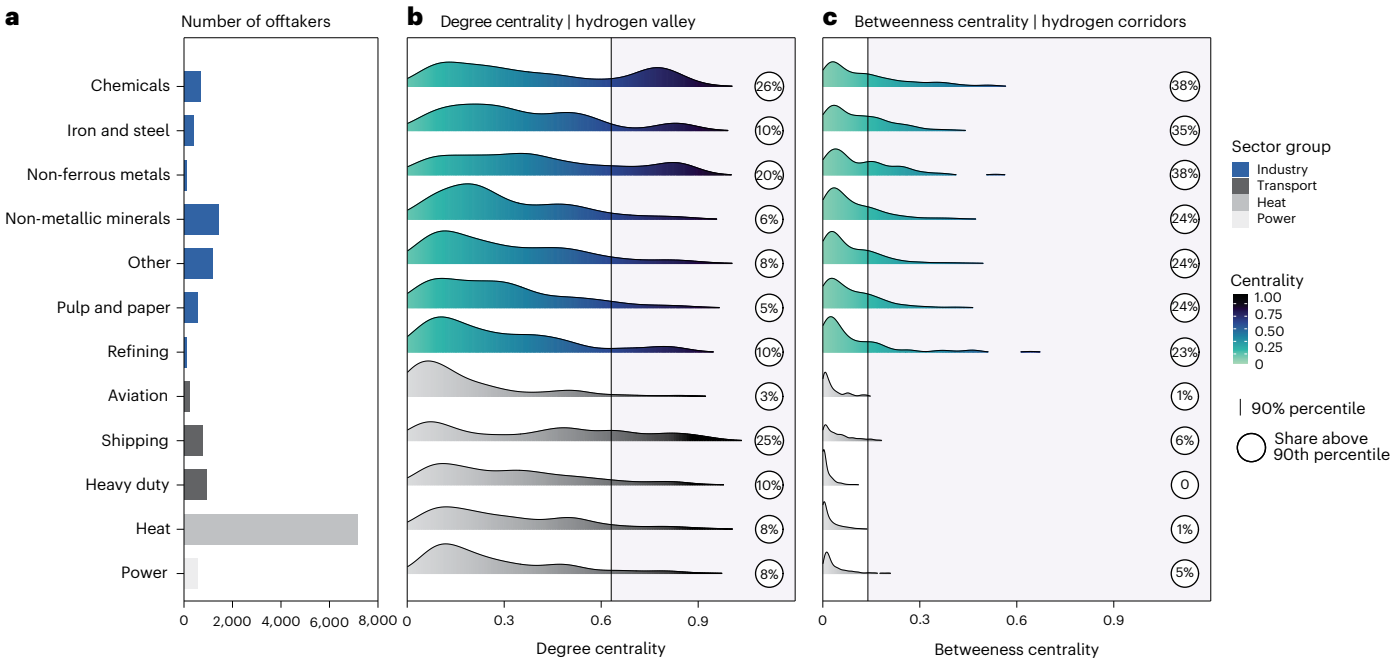

Fig. 4 | Spatial spillover potential of prospective green-hydrogen offtakers across sectors. a, Number of candidate offtakers included in each sector (total 14,108). Heavy-duty mobility offtakers are aggregated to NUTS-3 regions and heat offtakers to city level to avoid disproportionate effects on network metrics (Methods; Extended Data Tables 3 and 4). **b**,**c**, Sectoral distributions of centrality metrics, degree centrality (**b**) and betweenness centrality (**c**), shown as ridge plots. Colour intensity indicates centrality magnitude. Vertical lines denote the 90th percentile threshold, corresponding to the 10% most central installations across all sectors. Marginal circles indicate the share of installations within each sector belonging to this highest-centrality group. Values above 10% indicate a disproportionate concentration of highly influential installations. Spatial spillover potential is concentrated particularly among hard-to-abate industrial sectors. Metrics are calculated for 14,108 offtakers and standardized to a 0–1 scale.

are typically more cost-effective, such as power and heat). Lower saturation rates also weaken spatial spillovers because lower local diffusion reduces spillover pressure.

First, we present baseline projections of green hydrogen demand—including carbon pricing but no other policy interventions—across this matrix (Fig. 5). By 2050, demand in the restricted case is driven by hard-to-abate sectors, particularly chemicals (>80%) and iron and steel (>12%) (Fig. 5a). In the central case, demand expands to the transport sector (aviation and shipping) and in the extended case, to the power sector. Aggregate diffusion curves between 2024 and 2100 (Fig. 5b) follow the characteristic s-shaped associated with technology diffusion[53]. Of all scenario combinations, only the most optimistic (progressive cost + extended saturation) meets the EU's 2030 target of 20 Mt green hydrogen demand[3]. In the mean cost + central saturation scenario, diffusion barely takes off until 2030, with an expected demand of approximately 3 Mt (83% shortfall). Projections fall similarly short of the 2050 target (10% of final energy consumption, or 50 Mt): in the mean cost + central saturation scenario, expected demand amounts to approximately 29 Mt (43% shortfall). Achieving stated targets will require sustained policy intervention until at least the late 2030: In the central saturation scenario, achieving 2030 targets is consistent with green hydrogen costs of €71 MWh^{-1} (58% below the mean cost trajectory; Methods). This is despite escalating carbon price assumptions[54] (Supplementary Fig. 13): holding carbon prices constant almost entirely suppresses diffusion through 2050 (Supplementary Fig. 14).

Second, we evaluate a spatially informed demand-side intervention relative to this baseline in a controlled setting. We model a one-sided contract for difference (CfD) that covers the cost differential between green hydrogen and fossil incumbents. The allocation rule controls for cost and size differences through sector-level stratification (within which modelled cost competitiveness is identical) and quartiles of estimated 2050 hydrogen-specific energy use (Fig. 6a). Within each sector-size group, 10% of installations are targeted with the CfD. We compare a spatially informed intervention (prioritizing the 10% most central offtakers) with a spatially neutral strategy. For clarity, we present results for the mean cost and central saturation baseline (see Supplementary Figs. 15 and 16 for alternative baselines).

In this controlled setting, spatially informed interventions increase annual green hydrogen demand (in 2100) by about 6–10% (2.2–4.1 Mt; Fig. 6c) relative to a spatially neutral approach: although we stratify by size, targeting high-centrality offtakers shifts the composition of adopters towards installations with greater long-run demand potential. Because realized adoption and offtaker size may differ across targeting strategies, policy costs vary. We therefore compute policy effectiveness as the ratio of cumulative policy cost to cumulative additional hydrogen demand (Fig. 6e). By 2100, spatially informed interventions reduce the median cost per additional kilogramme of green hydrogen demand by 37–41% (€0.83–0.96 kg^{-1}) relative to spatially neutral interventions. Policy effectiveness advantages emerge from 2040 onwards: hydrogen demand differences arise early (when cost competitiveness is low), increasing policy expenditures. As local diffusion increases, spatial spillovers intensify, improving policy cost effectiveness. Demand differences resulting from the composition of supported offtakers also persist over time, further reinforcing this pattern. This effect holds for both operationalizations of spillover potential, degree centrality (hydrogen valleys) and betweenness centrality (hydrogen corridors). Our results are conditional on green hydrogen demand following similar diffusion patterns as natural gas power generation (Supplementary Note 2).

Third, we assess the impact of incorporating a spatially informed demand-side element into existing supply-side policy instruments. We model an EHB-style auction, where the minimum subsidy (cost competitiveness) rule is amended with a centrality criterion, weighted at 10% (Fig. 6b). The amendment increases annual demand in 2100 by up to 1.6% (0.6 Mt; Fig. 6e) and improves cost-effectiveness by 13–15% (€0.17–0.20 kg^{-1}; Fig. 6f). Despite introducing only a minor modification

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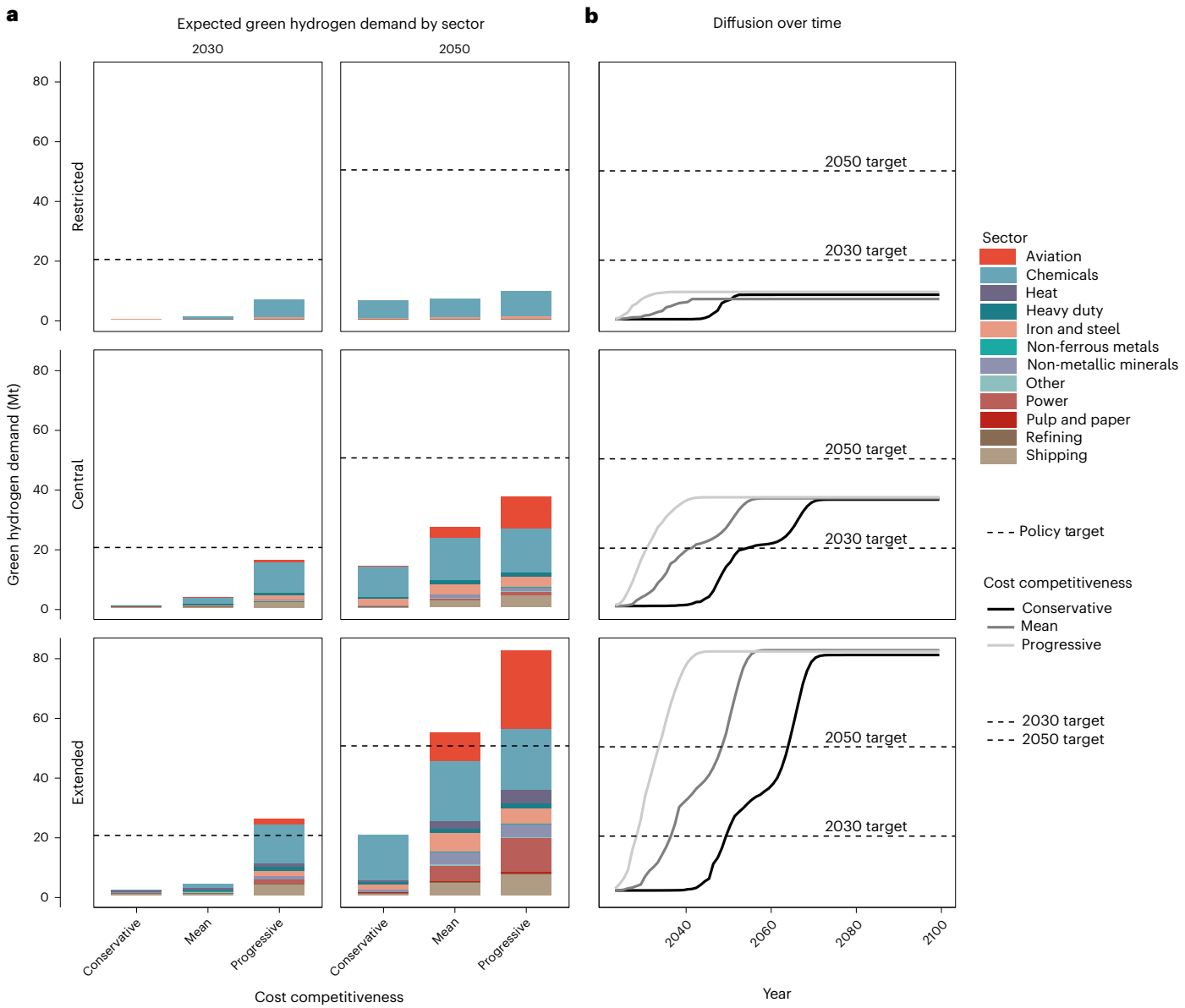

Fig. 5 | Baseline projections of green-hydrogen diffusion under carbon pricing. **a**, Projected green-hydrogen demand in 2030 and 2050 under combinations of green-hydrogen cost trajectories and sectoral saturation assumptions. Dashed lines indicate European hydrogen deployment targets of 20 Mt by 2030 and 50 Mt by 2050. Most scenarios remain below policy targets, except under the most optimistic assumption combination. **b**, Time evolution of green-hydrogen diffusion between 2024 and 2070 across saturation scenarios. Diffusion trajectories exhibit the characteristic s-shaped pattern associated with technology diffusion. Projections incorporate an escalating carbon price trajectory consistent with EU climate policy objectives and sector-specific hydrogen demand potentials. Results are based on 14,108 prospective offtakers.

to the cost competitiveness award rule, the effect reaches 20–25% of the controlled effect size, underlining its economic relevance. Results support adjusting rather than replacing existing policies: emphasizing cost competitiveness avoids disbursement spikes in early years, and cost competitiveness losses outweigh spillover gains when increasing the centrality criterion's weight beyond 20% (Supplementary Fig. 17).

Discussion and conclusion

In this paper, we assess how the spatial patterns of green hydrogen demand shape the evolution of Europe's prospective hydrogen economy and derive implications for spatially informed demand-side policies. Using natural gas power plants as a historical analogue, we show that both cost competitiveness (average marginal effect 14.5 pp per s.d.) and spatial spillovers (1.7 pp per s.d.) are positively associated with diffusion and strongly reinforce each other. When cost competitiveness is very low (lower than the tenth percentile, −€210 MWh^{-1}) and local diffusion is high (near full diffusion), spillover effects increase more than 20-fold. On the basis of these estimates, we construct baseline demand projections (excluding policy support beyond carbon pricing). In the central case, green hydrogen demand falls 83% short of the EU's 2030 target and 43% short of the 2050 target, underscoring the need for sustained policy support. Our results provide guidance for structuring this support and highlight the need for adjustments to the EU's existing policy portfolio.

First, we show that the EU's existing place-based policies, most prominently EU hydrogen valleys and corridors, are only weakly linked to modelled demand and do not fully exploit spillover potential. Spillover potential concentrates in a small set of industrial regions along the North Sea coast and the Rhine-Ruhr valley and in hard-to-abate sectors. In our >14,000 prospective offtaker network, more than half of those

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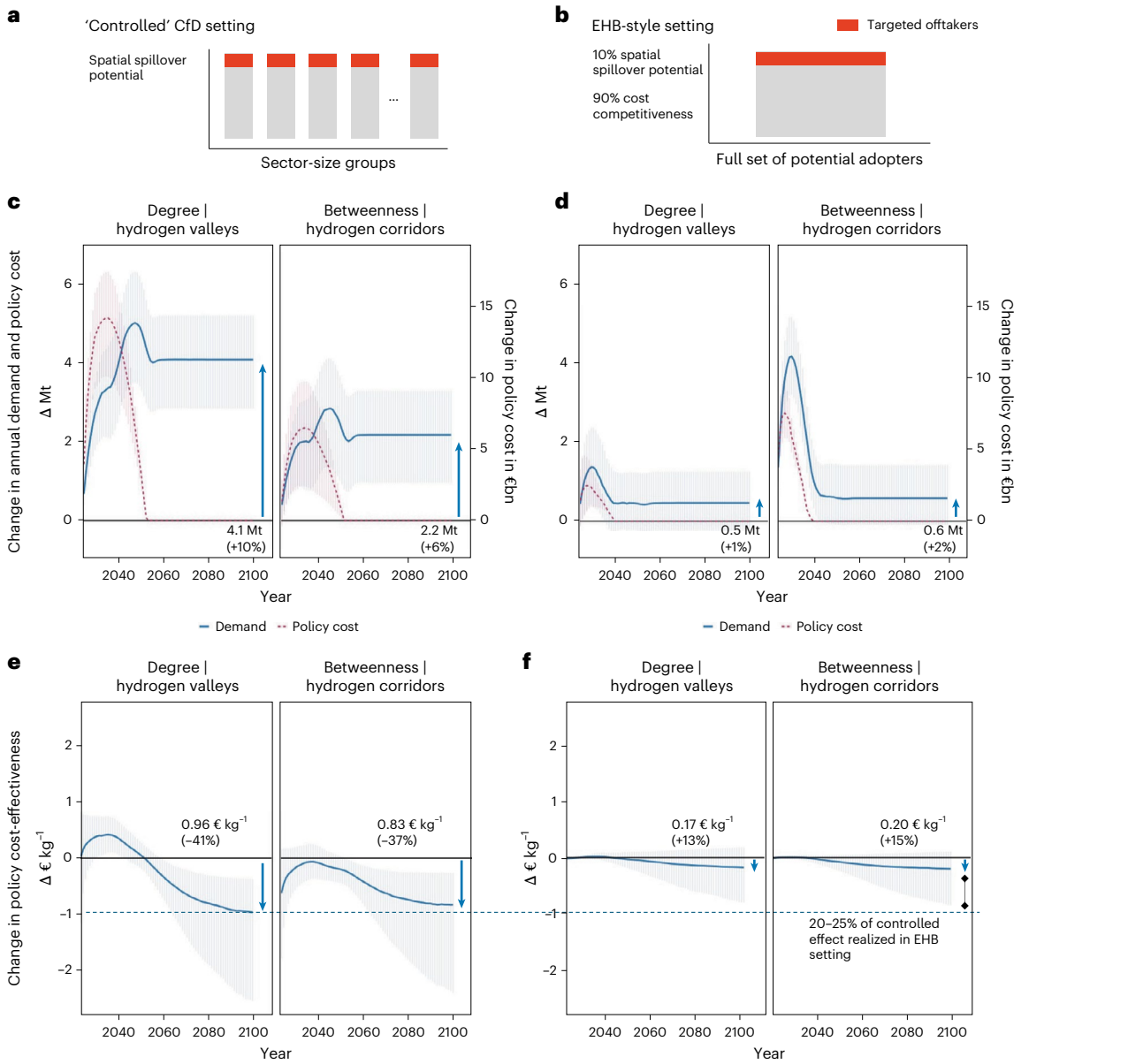

Fig. 6 | Effects of spatially targeted versus spatially neutral policy interventions. a,**b**, Design of policy interventions comparing spatially informed support mechanisms with spatially neutral approaches. Comparison of a spatially targeted CfD mechanism with a spatially neutral CfD under controlled sector-, cost- and size-matched conditions (**a**). Comparison of a spatially targeted auction mechanism (following the EHB setting) based on spillover potential with a spatially neutral auction (**b**). **c**,**d**, Differences in annual hydrogen demand and policy expenditure resulting from spatial targeting based on degree centrality (hydrogen valleys, **c**) and betweenness centrality (hydrogen corridors, **d**). Targeting high-spillover installations accelerates diffusion by triggering earlier adoption and reinforcing local spillovers. Effects depend on the interaction between cost competitiveness, spatial spillovers and sectoral saturation limits. **e**,**f**, Differences in policy cost-effectiveness expressed as euros per kilogramme hydrogen for spatial targeting based on degree centrality (hydrogen valleys, **c**) and betweenness centrality (hydrogen corridors, **d**). Higher values indicate lower cost-effectiveness. Spatial targeting improves long-term cost-effectiveness, with a proportion of the isolated targeting effect retained when applied within an infrastructure-based auction setting. In **e**, disbursement peaks early, as less competitive offtakers adopt and cost-effectiveness improves over time as spillovers materialize. In **f**, the cost-competitiveness criterion reduces this initial peak. Results are based on 14,108 prospective offtakers.

in the top degree centrality (hydrogen valley) decile are located in five regions in Belgium (Antwerp and East Flanders) and Germany (Düsseldorf, Cologne and Rheinhessen-Pfalz). One-quarter of offtakers in chemicals and shipping and about one-fifth in non-ferrous metals fall into the top centrality decile. Betweenness centrality (hydrogen corridors) yields similar patterns, providing clear targets for place-based and industrial policies[6,11], which also align with regional development goals: key areas (the Rhine-Ruhr valley, North Sea coast and Southern Poland) overlap with regions supported by the EU's €19.7 billion Just Transition Mechanism[55].

Our results imply that placing hydrogen valleys in regions with high spillover potential (by increasing the stringency of demand criteria in selection) could improve their effectiveness in catalysing green hydrogen economies. Infrastructure plans, such as the REPowerEU import corridors[50] and the industry-led European Hydrogen Backbone[51], extend far beyond these regions. Prioritizing high-spillover industrial links could improve investment targeting and reduce future underutilization (asset stranding risk) of the hydrogen grid. Shifts towards renewable-based production could reorganize global trade and the footprint of energy-intensive production[56,57]. How energy

and industrial policy address this issue could affect the green hydrogen demand networks discussed here. Recent EU industrial policy efforts such as the Clean Industrial Deal Industrial Accelerator Act point towards an effort to preserving existing industrial networks[58].

Second, our results demonstrate the benefits of extending supply-side schemes (EHB auctions) with spatially informed demand-side instruments or criteria. Auction awards do not necessarily convert into deployment. In offshore wind, the 2.4-GW Hornsea 4 project was halted despite a £59 MWh^{-1} CfD. In the EHB auction's 2025 iteration, only 20% of the initial budget (€1.2 billion) was contracted. Offtake risk—the availability of demand at expected prices—is a key barrier[59]: Ørsted's 70-MW FlagshipONE e-methanol project was cancelled 2 years into construction owing to a lack of viable offtake agreements, incurring a €190-million impairment loss[60] Demand-side instruments can increase conversion and improve allocational precision. EHB results indicate differences in median subsidy needs for transport and industry (€1.8 kg^{-1} versus €2 kg^{-1})[61], highlighting room for sectoral targeting. Spillovers further crowd in private investment by increasing nearby adoption without direct policy support. We add quantitative evidence: awarding CfDs to the 10% most central offtakers (controlling for sector, cost and size) improves median policy cost-effectiveness by up to 41% (€0.96 kg^{-1}) relative to a spatially neutral allocation. A total of 20–25% of the controlled effect (15%, €0.20 kg^{-1}) is realized when adding a centrality criterion (10% weight) to an EHB-style auction. These benefits materialize over time, requiring sustained policy commitment into the growth and slowdown phases of diffusion, where solar and wind policies have come under pressure[14]. Integrating the EHB's transparency mechanism, which matches hydrogen supply projects with potential offtakers, into EHB auction systems could help strengthen demand linkages.

Our results align with prior evidence on spatial spillovers in renewable generation[20,21], solar photovoltaics[22] and heat pumps[23], although these studies emphasize peer and neighbourhood effects alongside supply chain and knowledge spillovers. Although cost competitiveness is typically not modelled explicitly, they also identify similar interaction patterns (for example, between renewable portfolio standards and local resource endowments)[20].

We make several contributions to research and practice. We construct a geo-referenced database of >14,000 offtakers across industrial, transport, power and heating sectors, providing a resource for decarbonization analyses beyond green hydrogen. On this basis, we introduce three innovations. First, our bottom-up approach captures spatial spillovers and enables disaggregation by sector, region and installation. Second, we link adoption explicitly to the cost competitiveness of green hydrogen relative to fossil incumbents, enabling quantitative evaluation of place-based policies including EU hydrogen valleys and cost-based instruments such as (carbon) CfDs. Third, by empirically grounding the model, we address methodological shortcomings in earlier work[36]. Together, the data and modelling framework connect bottom-up modelling to system-level assessment and provide a platform transferable to other technologies shaped by spatial spillovers, such as CCUS and CO_2 networks.

Methods

This section has five parts. First, we describe the empirical model. Second, we present the construction of the green hydrogen offtaker database. Third, we outline the calculation of the network metrics used to measure spillover potential. Fourth, we describe the simulation procedure for the baseline green hydrogen demand projection and policy evaluation. Finally, we discuss limitations.

Empirical model

We begin by clarifying terminology, following Rogers' theory of innovation[53]. Adoption, or adoption probabilities, refer to installation-level decisions to switch from a fossil energy source to green hydrogen or one of its derivatives. Diffusion refers to the aggregate system share of green hydrogen or its derivatives. The two are directly linked: diffusion reflects the aggregate outcome of adoption decisions made by thousands of individual installations or offtakers.

For the empirical identification of the model, we use natural gas power plants as historical analogue (see Supplementary Note 3 for details on the choice of analogue). The sample includes all natural gas power plants deployed in the EU between 1961 and February 2026 as recorded in the S&P Capital IQ Power Plant database. We opt for commercial rather than open-source data for this analysis, as, contrary to, for example, the Joint Research Center (JRC) Open Power Plants database, S&P Capital IQ reports reliable and largely complete values for power plant commissioning dates, which are required for a diffusion analysis. This dataset has been widely used to address research questions requiring power plant-level data[62,63].

For specifying our empirical model, we model adoption as a function of cost competitiveness, spatial spillovers and distance to waterways and natural gas pipeline corridors,

$$P(A_{i,t}) = \phi\left(\beta_0 + \beta_1 C_{i,t} + \beta_2 S_{i,t} + \beta_3 D_i^{\text{water}} + \beta_4 D_i^{\text{pipe}} + \beta_5 S_{i,t} C_{i,t}\right), \quad (1)$$

where:

- $P(A_{i,t})$: probability of adoption for installation i in year t
- $A_{i,t}$: adoption at installation i in year t
- $\phi(\cdot)$: logistic link function
- $C_{i,t}$: cost competitiveness for installation i in year t
- $S_{i,t}$: spatial spillover (index) for installation i in year t
- D_i^{water}: distance from installation i to the nearest port (inland or maritime)
- D_i^{pipe}: distance from installation i to the nearest natural gas pipeline transmission corridor
- $S_{i,t}C_{i,t}$: interaction term capturing joint effects of spatial spillovers and cost competitiveness

For all locations, adoption as the dependent variable is defined as binary and equal to 1 if a natural gas power plant has been deployed at the location and 0 otherwise. Adoption is irreversible and only considered for the set of observed plants sites, meaning that in February 2026 the adoption status for all locations is equal to 1.

The selection of independent variables is based on the theory of diffusion of energy technologies. For energy technologies, diffusion typically occurs as a new technology displaces an incumbent one. A major driver of adoption is therefore the relative cost–risk trade-off between the new and incumbent options[13,64] (Supplementary Note 2). We include cost competitiveness as the primary technology-specific driver of adoption, defining it as the difference between the cost of the new technology and that of the incumbent. Details on the estimation of the cost-competitiveness measure are provided below. The rationale for considering spatial spillovers is explained extensively in the main article. In the context of regional policy interventions, spatial spillover pressure has been conceptualized as the intervention region's size relative to the overall market[44]. We transfer this metric to an installation level, by defining the spatial spillover index as the level of local diffusion relative to the global average. We calculate this as the weighted adoption status of neighbouring installations within a 120-km radius, which is then demeaned cross-sectionally. This eliminates effects from an aggregate increase in average adoption[65]. The radius is chosen on the basis of hyperparameter optimization on a validation set maximizing the area under the receiver operating characteristic (ROC) curve (true versus false positive rate)[66]. Results are robust to respecifying the spatial spillover index with alternative spatial weight definitions or different cutoffs. We include distance to waterways and distance to natural gas transmission pipelines as physical infrastructure access variables, as natural gas or hydrogen transmission could occur by way of pipeline (including repurposed natural gas pipelines), or by way of

water, in pressurized tanks or chemical carrier form[45]. Note that these are static measures, whereas the dynamic build-up of shared infrastructure is conceptually captured through the spatial spillover measure.

Our model relies on a direct link between adoption and cost competitiveness. This is consistent with the approach taken in many energy system simulations and techno-economic models that too rely on information on the cost of green hydrogen and competing technologies[30,31,67]. Cost competitiveness considerations also underlie—albeit only implicitly—the rate of diffusion assumptions that underpin the logistic models informing feasibility space studies[35,37]. Our model builds on and extends these concepts by making cost competition explicit—operationalizing cost competitiveness as the cost spread between green hydrogen and an incumbent technology—and taking an installation-level perspective that allows us to represent relational ties and spillovers between different offtakers.

Quantifying cost competitiveness requires comparing LCOEs across competing technologies. For natural gas power generation, this involves competition with coal, nuclear and renewable sources. The LCOE captures factors such as capital costs, fuel costs (including transport) or the capacity factor, many of which vary across space[68]. Measuring cost competitiveness as the aggregate spread between the LCOE of natural gas and one competing technology is therefore only of limited validity. Moreover, historical datasets on the LCOE of natural gas and competing technologies are extremely scarce. Existing time series combine multiple sources with data quality issues and methodological inconsistencies[43]. We address this by estimating cost competitiveness through a proxy based on a first-pass logit model that includes only spatial spillovers and physical infrastructure access. The residuals are then interpreted as a latent measure of cost competitiveness that is unobserved in the historical data,

$$\begin{aligned}\phi^{-1}(A_{i,t}) &= \beta_0 + \beta_1 C_{i,t} + \beta_2 S_{i,t} + \beta_3 D_i^{\text{water}} + \beta_4 D_i^{\text{pipe}} + \beta_5 C_{i,t} S_{i,t} + \varepsilon_{i,t},\\ C_{i,t} &= A_{i,t} - \phi\left(\hat{\beta}_0 + \hat{\beta}_1 \hat{C}_{i,t} + \hat{\beta}_2 \hat{S}_{i,t} + \hat{\beta}_3 \hat{C}_{i,t} S_{i,t} + \hat{\beta}_4 D_i^{\text{water}} + \hat{\beta}_5 D_i^{\text{pipe}}\right).\end{aligned} \quad (2)$$

Using proxies is consistent with established approaches in economic studies and is commonly used when data limitations constrain direct measurement of a variable[69,70]. Residuals can effectively capture a latent concept when that concept dominates the error term independently of the included variables and when the resulting proxy aligns with theoretical expectations in validation tests[71]. Because we control for both spatial spillovers and physical infrastructure access through distance to waterways and natural gas transmission pipelines, it is reasonable to assume that cost competitiveness drives the error term. Similar strategies have been used to measure market inefficiencies and non-competitive behaviour in power markets[72] and in other contexts where variables are difficult to measure directly, for example, to identify unusual armament patterns in political science[73].

To provide further evidence for the robustness of the proxy, we use an external measure of cost competitiveness, defined as the spread between the LCOE of natural gas and that of coal. For both LCOE time series, we use data collected by Way et al.[43], who aggregate several historical sources to time series ranging from 1982 to 2020 for natural gas and from 1948 to 2020 for coal. The data quality of these series is generally limited, with incomplete coverage and partially inconsistent assumptions regarding generation technologies and input costs[43]. Furthermore, the data reflect aggregate US LCOEs and are not directly applicable to a European model. Despite its limitations, the LCOE measure is highly related to our proxy (correlation coefficient of 0.7 and R^2 of 0.47).

In the second-pass regression we reintroduce the residuals to quantify the unexplained variation of the first-pass model, interpreted as a latent measure of cost competitiveness, in a form suitable for forward-looking simulation. As the residuals are a function of $A_{i,t}$, this produces perfect classification by construction. This is appropriate here, as the regression is used only to assign a coefficient to the residuals rather than generate new insights. To avoid overfitting, we introduce a random noise term with mean zero and an s.d. equal to one-fourth of the residuals' s.d. The noise level is selected via hyperparameter optimization following the same procedure used for the distance-threshold choice[66]. As the residual-derived cost-competitiveness term is unitless, we rescale it to match the simulation environment by assigning the same upper bound, lower bound and zero anchors as the competitiveness measures used in the simulation[65,66].

As $A_{i,t}$ is cumulative and non-reversible, it is subject to autocorrelation. We therefore implement the logit model using GEE and R's geepack package. GEE is a semiparametric generalized linear model for longitudinal data that provides consistent and unbiased coefficient estimates under weaker time-dependence assumptions than standard generalized linear models. Note that while we specify a first-order autoregressive (AR(1)) correlation structure, the estimates remain consistent and unbiased even if the real correlation structure deviates from AR(1)[74].

We estimate adoption for a set of observed plant sites, with proximity to waterways and pipeline corridors included as additional controls. Our analysis thus explains the timing of adoption of natural gas power plants at locations that are relevant adoption units, rather than the estimating the unconditional probability that a plant is ever sited at an arbitrary location. This is consistent with the scope of our analysis: including locations where no plant is ever built would not identify additional adoption events and shift the analysis towards a siting problem over a large set of potential locations. Identification in our analysis relies on variation in adoption timing across locations over time. Bias from not including additional locations beyond relevant adoption units arises only in cases where adoption timing, siting and the independent variables are jointly affected by unobserved events that are both local and time-varying. While we cannot fully rule out such confounding, we are confident that it does not materially affect our results.

Results are discussed in detail above (Main). We evaluate the discriminatory power of the model using the area under the ROC curve and mean standard error[66]. For the training set, the area under the ROC curve amounts to 0.998, and the mean standard error to 0.0155, indicating very high discriminatory power. This result follows directly from the specification of the model, as the second pass regression includes the transformed residuals of the first-pass regression as an additional regressor. The more relevant test is therefore to evaluate model performance using alternative measures of cost competitiveness. To that purpose, we replace it with the external LCOE measure discussed above. Discriminatory power declines in this specification (area under the ROC curve of 0.79, mean standard error of 0.19) but performance remains sufficiently robust to support its validity. Marginal effects calculated on the basis of this model are similarly consistent, with the relative importance of spatial spillovers increasing at the expense of cost competitiveness (Supplementary Fig. 8). Note that we also use this LCOE time series for hyperparameter (distance threshold and random noise term) optimization on the validation set. Further robustness checks show no concerns regarding multicollinearity (Supplementary Table 4) and spatial autocorrelation (Supplementary Fig. 9). Serial autocorrelation (Supplementary Fig. 10) patterns are consistent with the specification of $A_{i,t}$ as cumulative and non-reversible.

Offtaker database

For our analyses on the prospective EU hydrogen economy, we build an original database of green hydrogen offtakers across the EU, using the most recent spatially resolved open-source data available to us as of 31 December 2024. For this purpose, we define an offtaker as any installation or consumer currently using fossil energy sources that could be substituted with green hydrogen or one of its derivatives (such as e-methane, e-methanol or e-kerosene). We include offtakers from industrial, transport (aviation, shipping and heavy-duty),

power and heating sectors. A breakdown by sector and country of the full integrated database is presented in Extended Data Tables 3 and 4. Industry-level emission factors and hydrogen-specific energy consumption factors are presented in Extended Data Tables 5 and 6. A detailed documentation of the database build-up is provided in the Supplementary Methods.

Network metrics

We leverage network theory to assess the structure of Europe's prospective green hydrogen economy. In doing so, we represent offtakers as a spatial network, where each potential offtaker is a node, and edges between nodes represent influence through geographic proximity and relational ties. To characterize this network, we apply two centrality measures to reflect three different aspects of influence: degree centrality (measuring local influence and representing hydrogen valleys) and betweenness centrality (measuring mediating influence, representing hydrogen corridors)[48]. Details on the choice and construction of network metrics are provided in the Supplementary Methods. To make sure network metrics are not disproportionately reflected by a single sector, we recalculate them excluding heating installations, which make up approximately half of the dataset, and find no material changes (Extended Data Fig. 3).

Simulation

We build on the empirical model to generate forward-looking projections of green hydrogen demand. These projections serve as a baseline (excluding policy interventions beyond carbon pricing) against which to evaluate policy interventions. Each simulation year proceeds as follows: first, cost differentials between green hydrogen (or a derivative product) and the corresponding fossil incumbent are retrieved from forecast values and matched to each installation by sector. Second, the adoption status from the previous year is used to compute spatial spillover indices based on a 120-km distance threshold using R's FNN and Matrix packages; as in the empirical model, these indices are demeaned cross-sectionally to remove aggregate trends in diffusion.

Third, for each installation i in sector s, the probability of adoption is computed as the product of the empirical logit prediction and a sector-level adjustment factor that aligns long-run adoption with the sector's saturation level β_{6s}. Formally,

$$P_{i,t} = \phi\left(\beta_0 + \beta_1 C_{i,t} + \beta_2 S_{i,t} + \beta_3 D_i^{\text{water}} + \beta_4 D_i^{\text{pipe}} + \beta_5 C_{i,t} S_{i,t}\right) \cdot F_{s,t}, \quad (3)$$

where $C_{i,t}$ denotes cost competitiveness, $S_{i,t}$ spatial spillovers and $F_{s,t}$ is defined as

$$F_{s,t} = \max\left(0, \frac{\beta_{6s} - \bar{A}_{s,t}}{1 - \bar{A}_{s,t}}\right), \quad (4)$$

with $\bar{A}_{s,t}$ denoting the mean adoption rate in sector s at time t.

On the basis of the simulated adoption probability, adoption is then realized as

$$A_{i,t} = \begin{cases} 1, & \text{if } P_{i,t} \geq U_{i,t}, \quad U_{i,t} \sim \mathcal{U}(0,1), s \notin \mathcal{C}, \\ 0, & \text{if } P_{i,t} < U_{i,t}, \quad s \notin \mathcal{C}, \\ P_{i,t}, & s \in \mathcal{C}, \end{cases} \quad (5)$$

where $\mathcal{C}$ denotes a set of 'continuous-adoption' sectors (aviation, shipping and heavy-duty transport, where green hydrogen may be adopted partially for only a subset of planes or ships) and $U_{i,t}$ is a random draw from a uniform distribution. All results (probability, adoption, cost gap and spatial influence) are stored annually for post-simulation analysis. To implement the simulation, forward-looking estimates of cost competitiveness are required. As in the empirical model, cost competitiveness is defined as the cost difference between green hydrogen (or a derivative) and the fossil incumbent in each sector and year (Supplementary Table 5). We rely on data from Odenweller and Ueckerdt[6] and extend these projections to 2100 (Supplementary Fig. 11). To assess whether spatially informed policies yield superior policy outcomes relative to spatially neutral policies, we simulate demand-side policy interventions in two settings. First, we assess a one-sided CfD in a controlled setting designed to isolate the effect of spatial targeting while holding sector, technology cost conditions and installation size approximately constant. Second, we evaluate a more realistic auction design that mirrors the EHB auction mechanism. We show both approaches because they serve different purposes: the controlled setting isolates the effect of spatial targeting under comparable conditions, while the EHB-style auction assesses whether spatial targeting can also improve outcomes under a policy allocation rule closer to existing subsidy practice. Further details on the simulation procedure (including the operationalization of cost competitiveness) and the specification of the policy interventions are reported in the Supplementary Methods.

Limitations

While we conduct extensive robustness checks to ensure the validity of our work, some limitations necessarily persist. Using historical analogues is a well-established technique for empirically grounded analysis when robust historical data on the target technology—in this case green hydrogen—are unavailable and has been widely used in feasibility studies for green hydrogen[35] and other technologies such as CCUS[37]. As with any analogue, some differences in characteristics and diffusion patterns are likely to persist. We therefore make our choice of natural gas power plants transparent and reproducible (Supplementary Note 3) and provide a robustness check by re-estimating our model using cogeneration and wind plants (Supplementary Note 4), which yields consistent results.

The empirical analysis also requires a measure of cost competitiveness. For natural gas power plants, this is the LCOE difference relative to competing technologies (coal, nuclear, hydro, wind or solar). Historical LCOE time series are of uneven quality and do not fully capture the heterogeneity of this competition[43]. To address this, we use a residual-based latent measure of cost competitiveness. While such approaches are common when direct measurement is difficult—including in energy research[72]—they are only valid when the latent signal dominates the residuals. Although we are confident this is the case here, we cannot fully exclude the persistency of some residual noise.

Our original database of 14,108 green hydrogen offtakers is a key contribution to both research and practice. The database covers approximately 70% of EU emissions and therefore most major use cases for green hydrogen. Some simplifications are unavoidable. Certain applications are excluded where alternative decarbonization options have clear economic or technological advantages (such as passenger vehicles) or where their contribution to emissions and energy use is minor (such as cargo-only flights). Given the scale of the study, we rely on (sub)industry-level emission factors and hydrogen-specific energy consumption factors, which may not fully reflect heterogeneity in activities and production processes across installations.

For the forward-looking analysis, we rely on sector-level technology pairings, which again cannot capture all plant-level differences. Production pathways vary across energy-intensive sectors. In iron and steel, for instance, upstream material can be produced via natural-gas-based direct reduction or via coke-fuelled blast furnaces[75]. In non-ferrous metals such as copper, zinc and lead, coal remains widely used for roasting and smelting and it also fuels rotary kilns in cement manufacturing[76]. Since our focus is on how geography and spatial spillovers shape diffusion rather than on detailed plant-level cost heterogeneity, we abstract from these process-specific differences.

Finally, we incorporate competition from alternative decarbonization technologies through saturation rates that cap sector-level adoption rather than embedding this competition directly into the

cost-competitiveness variable. While this is the more robust approach (see the 'Simulation' section), it still abstracts from process- and installation-level heterogeneity in cost competitiveness. As making plant-level predictions is not the purpose of this paper, this simplification is appropriate in the present case. An analysis that extends cost competitiveness to a process or installation level in given sectors of interest could be a promising direction for future research. We provide detailed considerations of our choice of this approach and the derivation of saturation rates in Supplementary Note 6.

Data availability

For the empirical analysis of natural gas power plant diffusion, we use data from S&P Capital IQ, a commercial data source, which we accessed via a university-wide subscription license held by the Vienna University of Economics and Business. Holders of a subscription can access the dataset via S&P Capital IQ Pro, using the Power Plant Units Screener function and filtering for European Union countries. We also use cost competitiveness data from Odenweller and Ueckerdt[6], which in its original form is available via GitHub at https://github.com/aodenweller/green-hydrogen-gap/. For the robustness check with external LCOE data, we use data shared with us by Way et al.[43]. For the network and simulation analysis, we use our original database of green hydrogen offtakers (Methods). In the same repository, we also make available a more detailed overview of the composition of emissions factors and hydrogen-specific energy consumption factors. The full database, as well as a more detailed overview of the composition of emissions factors and hydrogen-specific energy consumption factors, is available via GitHub at https://github.com/crumpelnik/h2-spatial-assessment-eu and via Zenodo at https://doi.org/10.5281/zenodo.21394321 (ref. 77).

Code availability

The code for running the analysis and building the figures in this paper is available via GitHub at https://github.com/crumpelnik/h2-spatial-assessment-eu in the form of R Jupyter notebooks.

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Author contributions

C.R. developed the research question and methodology, with contributions from B.Z. and K.S. C.R collected the data, performed the analysis and created the figures. C.R., B.Z. and K.S. interpreted the results. C.R. wrote the paper with review and editing from B.Z. and K.S. K.S. supervised the project.

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Competing interests

The authors declare no competing interests.

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Extended Data Table 1 | Generalized estimating-equation models of natural-gas plant adoption

Variable	Estimate	SE	95% CI	Wald χ^2	P
First pass					
Intercept	−0.168600	0.013058	[−0.194177, −0.143000]	166.67	$<2\times10^{-16}$***
Spatial spillovers (S_i,t)	2.007000	0.111278	[1.788872, 2.230000]	325.29	$<2\times10^{-16}$***
Distance to waterways (D_i^water)	−0.000368	0.000151	[−0.000664, −0.000071]	5.91	0.0151*
Distance to pipeline corridors (D_i^pipe)	−0.000044	0.000108	[−0.000256, 0.000168]	0.16	0.6851
Second pass					
Intercept	−0.851000	0.032366	[−0.914379, −0.788000]	691.24	$<2\times10^{-16}$***
Cost competitiveness (C_i,t)	0.057100	0.000524	[0.056058, 0.058100]	11869.07	$<2\times10^{-16}$***
Spatial spillovers (S_i,t)	9.810000	0.318167	[9.183688, 10.400000]	950.14	$<2\times10^{-16}$***
Distance to waterways (D_i^water)	−0.002260	0.000375	[−0.002998, −0.001530]	36.41	1.60×10^{-9}***
Distance to pipeline corridors (D_i^pipe)	0.000063	0.000319	[−0.000561, 0.000688]	0.04	0.843
Interaction: C_i,t × S_i,t	−0.015000	0.003068	[−0.020986, −0.008960]	23.82	1.06×10^{-6}***

The models use n = 146,706 observations from 3,493 installation-level clusters, with a maximum cluster size of 54. The first-pass model includes spatial spillovers and distances to waterways and pipeline corridors. The second-pass model additionally includes cost competitiveness and its interaction with spatial spillovers. Estimates are log-odds coefficients with installationclustered robust standard errors and 95% Wald confidence intervals. Wald statistics equal $(\hat{\beta}/\mathrm{SE})^2$ and correspond to two-sided tests of H_0: $\beta = 0$. For the first-pass model, the estimated AR(1) correlation parameter is $\hat{\alpha} = 0.8733$ (SE = 0.001669), and the scale parameter is 0.9928 (SE = 0.004274). For the second-pass model, $\hat{\alpha} = 0.0223$ (SE = 0.0949), and the scale parameter is 0.751 (SE = 3.19). Exact P values are reported where available; values below the numerical reporting threshold are shown as $P < 2\times10^{-16}$. No adjustment was made for multiple comparisons. ***P < 0.001, **P < 0.01, *P < 0.05 and · P < 0.1.

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Extended Data Table 2 | Sector-specific saturation values for hydrogen adoption across three scenarios

Sector	Restricted	Central	Extended
Aviation	0.00	0.35	0.80
Chemicals	0.35	0.70	0.90
Heat	0.00	0.00	0.05
Heavy-duty trucks	0.00	0.25	0.35
Iron & steel	0.20	0.40	0.70
Non-ferrous metals	0.00	0.25	0.50
Non-metallic minerals	0.00	0.20	0.70
Other	0.00	0.05	0.10
Power	0.00	0.10	1.00
Pulp & paper	0.00	0.00	0.70
Refining	0.45	0.60	0.75
Shipping	0.00	0.35	0.80

Saturation rates cap the diffusion of green hydrogen in a specific sector to reflect competition with alternative decarbonization technologies such as direct electrification, CCUS and biomass. The derivation of saturation rates is documented in Suppl. Note 6 (Suppl. Tables 6–17). For the restricted case, non-zero saturation rates are limited to sectors with no or few alternative decarbonization options. The extended case is designed as an upside case that raises and broadens saturation levels to include sectors where hydrogen is generally considered less competitive, such as power and heat.

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Extended Data Table 3 | Overview of hydrogen offtakers by sector

Sector	Installations (n)	Total hydrogen-specific energy consumption (kt)	Average hydrogen-specific energy consumption (kt)
Heat	7,149	89,758	12.6
Non-metallic minerals	1,417	6,299	4.45
Other	1,190	2,846	2.39
Heavy duty (aggregated)	920	4,735	5.15
Heavy duty	*72,692*	*4,762*	*0.0655*
Shipping	783	11,399	14.6
Chemicals	681	22,042	32.4
Pulp & paper	565	5,659	10.0
Power	552	11,181	20.3
Iron & steel	406	8,498	20.9
Aviation	236	33,086	140.0
Non-ferrous metals	106	528	4.98
Refining	103	273	2.65
Total	**14,108**	**1,96,305**	**13.9**

Offtakers denote installations and locations in hard-toabate industrial sectors, aviation, shipping, heavy-duty transport, power and heating sectors that could switch from the use of fossil energy sources to green hydrogen or one of its derivatives. Details on database construction are reported in Suppl. Methods.

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Extended Data Table 4 | Overview of hydrogen offtakers by country

Country	Installations	Hydrogen-specific energy consumption	
		Total, kt	Average, kt
Germany (DE)	3,365	41,485	12.3
France (FR)	1,788	27,640	15.5
Italy (IT)	1,723	22,489	13.1
Spain (ES)	1,380	18,178	13.2
Belgium (BE)	881	10,209	11.6
Poland (PL)	776	11,426	14.7
Netherlands (NL)	598	15,991	26.7
Romania (RO)	394	3,467	8.8
Portugal (PT)	381	3,519	9.24
Sweden (SE)	348	6,370	18.3
Hungary (HU)	306	3,595	11.7
Greece (EL)	302	4,182	13.8
Czechia (CZ)	299	4,167	13.9
Austria (AT)	261	5,214	20.0
Finland (FI)	231	4,312	18.7
Denmark (DK)	194	2,779	14.3
Ireland (IE)	169	2,721	16.1
Bulgaria (BG)	159	1,533	9.64
Slovakia (SK)	140	1,611	11.5
Croatia (HR)	119	898	7.55
Lithuania (LT)	88	1,188	13.5
Slovenia (SI)	61	729	12.0
Latvia (LV)	50	881	17.6
Estonia (EE)	33	557	16.9
Cyprus (CY)	23	508	22.1
Luxembourg (LU)	22	437	19.8
Malta (MT)	17	219	12.9
Total	**14,108**	**1,96,305**	**13.9**

Offtakers denote installations and locations in hard-toabate industrial sectors, aviation, shipping, heavy-duty transport, power and heating sectors that could switch from the use of fossil energy sources to green hydrogen or one of its derivatives. Details on database construction are reported in Suppl. Methods.

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Extended Data Table 5 | Emission factors for industrial sectors by subsector

Sector	Subsector	Emission factor (tCO_{2e}/t)
Chemicals	Chemicals (general)	0.99
	Inorganic chemicals	1.27
	Ammonia	1.57
	Nitric acid	0.23
	Soda ash	0.75
	Carbon black	1.49
	Organic chemicals	0.67
	Adipic acid	2.12
	Plastics	0.64
	Pharmaceuticals	0.65
Iron & steel	Integrated	1.13
	Processing	0.24
	Iron casting	0.28
Non-ferrous metals	Non-ferrous metals (general)	1.59
	Aluminium	1.46
	Copper	1.40
	Lead, zinc and tin	1.92
Non-metallic minerals	Non-metallic minerals (general)	0.66
	Cement (clinker)	0.70
	Ceramics	0.10
	Refractories	1.80
	Glass	0.32
	Fibreglass & mineral wool	0.50
	Lime and dolime	0.76
	Plaster and gypsum	0.09
Pulp & paper	Pulp & paper (general)	0.20
	Paper	0.22
	Cartonboard	0.20
	Pulp	0.05
Refining	Refining (general)	0.41

Emissions factors are based on the EU Emissions Benchmark for the years 2021-2025 of phase 4 of the EU ETS. Values denote metric tonnes of CO2 equivalent per tonne of output.

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Extended Data Table 6 | Hydrogen-specific energy consumption by sector and subsector

Sector	Subsector	Fuel	Feedstock	Total
		(GJ/t)	(GJ/t)	(GJ/t)
Chemicals	Chemicals (general)	2.68	27.11	29.79
	Inorganic chemicals	3.29	10.21	13.50
	Ammonia	0.00	21.31	21.31
	Nitric acid	0.00	5.97	5.97
	Carbon black	64.80	0.00	64.80
	Soda ash	11.30	0.00	11.30
	Organic chemicals	2.20	40.41	42.61
	Adipic acid	21.60	0.00	21.60
	Plastics	6.07	0.00	6.07
	Pharmaceuticals	1.00	5.22	6.22
Iron & steel	Integrated	14.98	6.80	21.78
	Processing	2.48	0.00	2.48
	Iron Casting	2.48	0.00	2.48
Non-ferrous metals	Non-ferrous metals (general)	2.27	0.00	2.27
	Aluminium	12.02	0.00	12.02
	Copper	8.03	0.00	8.03
	Lead, Zinc and Tin	2.27	0.00	2.27
Non-metallic minerals	Non-metallic minerals (general)	4.54	0.00	4.54
	Cement	4.32	0.00	4.32
	Ceramics	3.07	0.00	3.07
	Refractories	5.38	0.00	5.38
	Glass	8.39	0.00	8.39
	Fibreglass & mineral wool	4.93	0.00	4.93
	Lime and Dolime	3.71	0.00	3.71
	Plaster and Gypsum	1.08	0.00	1.08
Pulp & paper	Pulp & paper (general)	3.26	0.00	3.26
	Paper	6.11	0.00	6.11
	Cartonboard	4.97	0.00	4.97
	Pulp	3.26	0.00	3.26
Refining	Refining (general)	0.00	0.43	0.43

Values denote gigajoules of hydrogen per tonne of output (GJ/t). Hydrogen-specific energy consumption factors are based on values reported by Neuwirth et al[32], Kiemel et al[78], and for some chemical subsectors the IEA [77,79]. For some sectors energy consumption factors are aggregated / averaged by activity levels. For non-classified activities, the fuel and heat benchmarks are used to estimate energy input. These amount to 0.04 MJ per t CO2 equivalent for fuel and 0.05 MJ per t CO2 equivalent for heat. The hydrogenspecific energy consumption factors for non-industrial sectors (transport, power and heat) are reported separately in Suppl. Methods.

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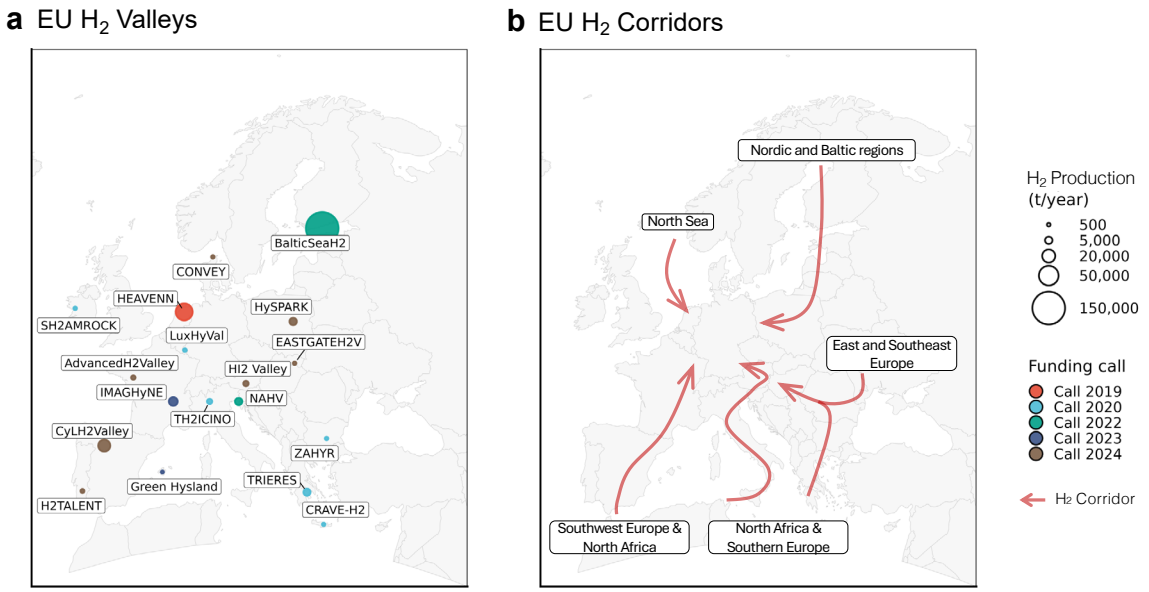

Extended Data Fig. 1 | EU-designated hydrogen valleys and hydrogen corridors. a EU-designated hydrogen valleys (up to 2024 call). hydrogen valleys outside the EU (Iceland, UK, Türkiye) are excluded. Bubble size denotes production target in tonnes per year. **b** EU hydrogen corridors. The EU has officially designated three import corridors (North Sea, Mediterranean, Ukraine) as part of RePowerEU[50]. The visualized hydrogen corridors correspond to the operationalization of these corridors as per the European hydrogen backbone study[57]. Basemap data from Natural Earth (https://www.naturalearthdata.com).

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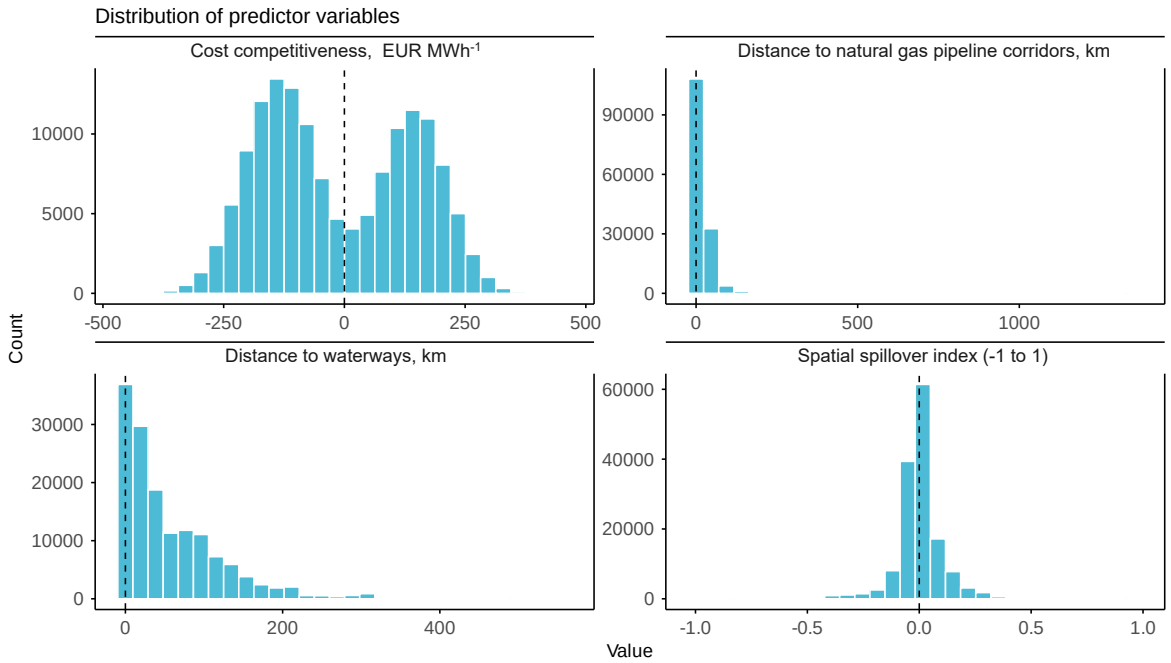

Extended Data Fig. 2 | Distribution of predictor variables in the empirical model. The histograms show the distribution of the independent variables included in the empirical model. Distributions of distance to pipeline corridors and waterways in particular deviate substantially from a normal distribution. Note that we use a GEE estimation procedure, which is semiparametric and does not rely on distribution assumptions in independent variables.

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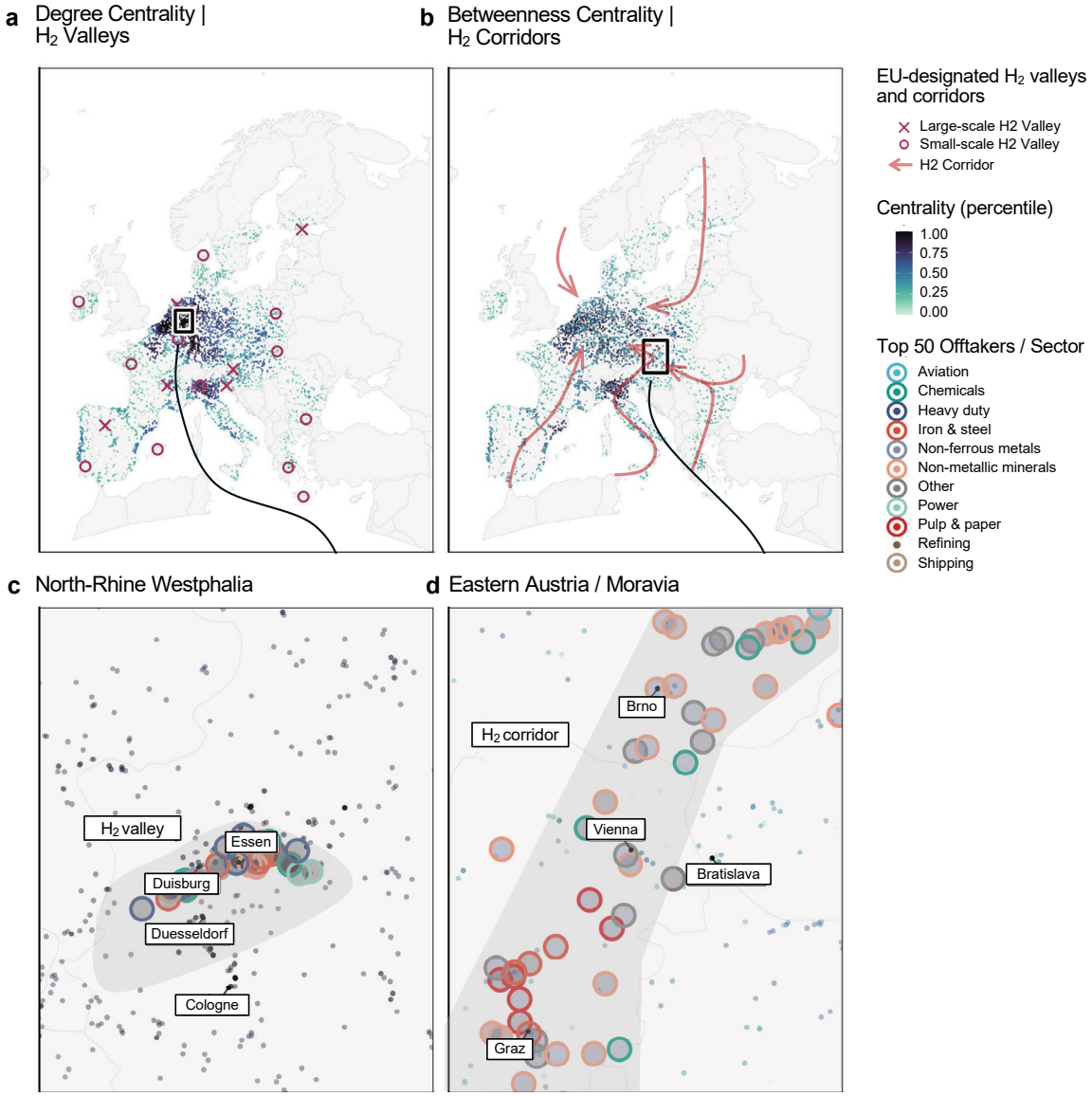

Extended Data Fig. 3 | Spatial spillover potential of green hydrogen offtakers across regions excluding heat. a-b EU-wide distribution of degree centrality (hydrogen valleys) and betweenness centrality (hydrogen corridors) excluding heat. Red markers indicate the location of hydrogen valleys as designated by the EU: large-scale valleys (more than 4 kt demand, ×) and small-scale valleys (0.5–4 kt demand, ˚).25 Red arrows indicate hydrogen import corridors defined by the EU as visualized by the European hydrogen backbone.57 The distribution is virtually unchanged compared to the version including heat. **c-d** Zoom-in on exemplary regions (North-Rhine Westphalia, and Eastern Austria/Moravia) illustrating local distributions. The 50 offtakers with the highest centrality scores are shown with larger point sizes, and industry categories are indicated by outlines around these points. Remaining points in the zoom-ins are shown in the same centrality-based color grading used in the EU-wide maps. Again, changes compared to the version including heat are minimal. Metrics are based on 6,959 offtakers and standardized to a zero-to-one scale to improve comparability. Basemap data from Natural Earth (https://www.naturalearthdata.com).