Social Influence and Spatio-Temporal Diffusion of New Durable Products: The Toyota Prius Hybrid Electric Vehicle in the United States

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Abstract

New products and ideas often exhibit heterogeneity in spatio-temporal diffusion, including spatial clustering at multiple scales. For example, adoption of the Toyota Prius hybrid electric vehicle is far higher on the US West and East coasts than in the Midwest; adoption clusters are also observed at the city scale. Does heterogeneity in adoption arise from differences in local conditions and adopter preferences, such as gasoline prices, affluence or political affiliations, or from endogenous social influence processes that build consumer familiarity with new products? The answer conditions policies to promote the adoption of technologies, for example, to mitigate greenhouse gas emissions. Resolving this question is challenging because information conditioning individual adoption decisions is communicated through multiple channels, including interpersonal interactions, direct experiences with the product, media attention, and advertising. We develop a novel model in which spatio-temporal diffusion arises from the interaction of product utility and social exposure across multiple geographic scales. We test the model on the diffusion of the Prius in 4 US cities, selected to capture variation in local conditions and the actual extent of Prius adoption observed, using a dataset capturing all new Prius registrations at the ZIP code level during the first decade of its introduction. Variation in Prius adoption is primarily explained by social influence through local interactions within each ZIP code, amplifying underlying heterogeneities in the utility consumers derive from the Prius. Our analysis highlights the importance of jointly representing local conditions and social influence at different scales to explain adoption clustering.

Keywords: spatial diffusion, social contagion, hybrid electric vehicles, fuel economy

1 Introduction

The diffusion of many promising green technologies is slow and uneven (1-3). Attempts to improve adoption, critical to meet environmental regulations or mitigate greenhouse gas emissions, often have limited impact (4-7). For example, adoption of the Toyota Prius hybrid electric vehicle in the United States is highly clustered, with high adoption on the West Coast and mid-Atlantic coast, and low adoption in between. Heterogeneity in adoption is also observed at the local level. In the San Francisco Bay Area, Prius adoption is high in San Francisco, Berkeley and around Palo Alto, but negligible in Daly City and Hayward, less affluent urban areas that lie in-between. Effective policies to promote adoption for both governments and firms depend on understanding the underlying patterns by which new products, practices, and ideas spread across time and space - a longstanding puzzle to social scientists.

Two compelling theories may explain clustered adoption patterns of products like the Prius. First, correlated patterns of adoption may result from geographical variations in product utility e.g., variations in gasoline prices or political values (11-14), explained in part by homophily—the tendency of people to associate with others who are similar (15). Alternatively, clustering may result from social influence, meaning that a consumer may be more likely to purchase a product if others with whom they are socially or spatially proximate have previously purchased that product. The classic theory of innovation diffusion explains the spatially aggregated stylized pattern of S-shaped growth in cumulative adoption as a social contagion process analogous to the spread of infectious diseases: early adopters generate word-of-mouth about to the product, leading to further sales and a still larger adopter population in a positive feedback (8-10); adoption ceases when the population of potential adopters is depleted. Similar processes may explain spatial variation in adoption at the local level. Understanding the origins of spatial heterogeneity in adoption is important both theoretically and practically. Strategies to promote the spread of novel products and ideas, including the deployment of clean technologies (5, 16, 17), depend on the extent to which consumer decisions are driven by social and environmental factors.

Theories that explain the role of social influence in clustered adoption must account not only for local conditions, but also for the nature of social influence driving adoption. For simple and low cost products, a single information channel such as social media may dominate social contagion (15). However, for durable products such as automobiles or solar photovoltaic panels, the build up of consumer consideration is likely to involve repeated exposure through multiple channels over time (16, 18-20)), because: (i) their use deviates from established social norms (21, 22); (ii) they have high attribute complexity (23); and (iii) they are often expensive and difficult to evaluate (24-26). While identifying each individual social influence mechanism is prohibitive in such cases, we can generate insights about the role of social influence in clustered spatiotemporal diffusion by comparing models with different assumptions about the spatial nature of social influence (27).

Social exposure to new products may play out over a range of spatial scales, each offering different forms of information transmission (20). Local contact between potential adopters and adopters offers occasions for direct observation of the product (8) or trial use (28, 29). Social proximity has been shown to be important in contexts ranging from knowledge spillovers in entrepreneurship (30), norm breaking behavior including crime, smoking, and housing foreclosures (31-33), and the adoption of agricultural (34, 35) and clean-tech innovations (36, 37) including hybrid electric vehicles (38). Information about products or practices may transfer between people at intermediate scales as individuals mix through travel or migration (39), or, as others observe behavior by influential agents, or "vanguards" (40-43), as observed in voting behavior (43, 44) and book sales (45). Finally, at the macro-level, social media allows the spread of information among socially proximate but geographically distant individuals. Media attention can also amplify social proof signals of "hot" products (46, 47).

We develop a generalized model of new product diffusion to examine spatio-temporal variation in the adoption of durable goods. In the model, adoption decisions are influenced by local conditions as well as social influence from adopters to potential adopters, at different spatial scales. We define a consumer choice structure that is consistent with classic discrete choice models (48). However, we relax the assumption of these models that consumers have full information about the utility of product adoption. Instead, we model the accumulation of consumer *willingness to consider* a new product behaviorally (16). Willingness to consider captures the population-level propensity to consider a product in purchase decisions, consistent with consideration set theory (19, 49), resulting from repeated exposure to and experience with the product. The model is flexible regarding how this exposure varies across spatial scales.

We apply the model to the diffusion of the Toyota Prius hybrid electric vehicle (HEV) in the United States, quantifying the roles of and interactions between variation in local conditions and social influence in explaining spatial and temporal variation in adoption. Introduced in the US in July 2000, the Toyota Prius has dominated the HEV market, accounting for more 50% of the 2 million hybrid vehicles sold in the United States since 2000 (50). Famous for high fuel economy and as a symbol of 'green' motoring (51, 52), the Prius, with its novel drivetrain, was a break not only from the long-dominant internal combustion engine technology, but a cognitive break in our conception of the car—automobiles transcend their instrumental use, signaling our style, values and socioeconomic status. Nationally, Prius sales have followed the commonly observed S-shaped pattern of innovation diffusion. However, diffusion is highly heterogeneous with clustered adoption observed at both the national and regional scales (Fig. 1).

We compare four models that capture social influence at different geographic scales, ranging from aggregate social influence (at the regional level), to social influence only within each individual neighborhood (defined at the 5 digit ZIP code level), and two models that combine neighborhood-level social influence with regional influence from other neighborhoods in the city. To estimate the models we develop a unique dataset comprising quarterly new vehicle registrations by ZIP code, and geospatial data on a range of demographic and market factors to control for heterogeneity in local conditions (e.g., affluence, gasoline prices, etc.). We evaluate models for 4 US cities that we strategically select using theoretical sampling (53) to capture variation in: (i) the perceived favorability of the demographic and market environment to hybrid vehicle adoption, and (ii) the actual extent of Prius adoption observed. These cities are the San Francisco Bay Area (favorable environment / high adoption), Atlanta (favorable environment / low adoption), Phoenix (unfavorable environment / high adoption) and Dallas-Forth Worth (unfavorable environment / low adoption). Our design thus examines the spatiotemporal diffusion of a radical and norm-breaking product in a range of settings with distinct conditions and diffusion patterns.

We find that social influence is critical for explaining the regional variation in Prius adoption observed in each of the four cities, with local social influence being dominant. These positive feedbacks amplify heterogeneity in Prius utility deriving from variation in local conditions. More generally, the importance of local social influence in building consumer consideration suggests that first-hand exposure is critical for durable products that are typically complex and expensive, including many eco-friendly technologies. Policies to promote the adoption of unfamiliar new technologies needed to achieve important environmental goals such as reductions in greenhouse gas emissions have typically focused on economic incentives such as tax credits in an attempt to increase affordability. Such policies have worked in some areas but not in others, resulting in slow and uneven adoption. Our results suggest broad uptake of these technologies also requires policies to strengthen the social processes that condition local exposure to the product and build the willingness of consumers to consider adoption.

2 Model

Our model explicitly distinguishes between the factors that affect the utility of the products available to consumers and the processes of social influence that condition consumers' willingness to consider those alternatives, including new products, in their purchase decision (16). A new product may offer superior utility, but will not be chosen unless consumers include that product in their consideration set. Willingness to consider is strongly conditioned by social processes, norms and habit (19, 54, 55). In our model, consumer choice occurs within a 'neighborhood' x, the smallest scale of spatial disaggregation, and results from the interaction of consideration with product utility, both of which are spatially disaggregated. Consideration integrates various channels of social influence, each with its own spatial signature. For example, direct observation of the product in use may be mostly local, while advertising and media reports may be regional or national. The utility of each product in neighborhood x depends on the inherent attributes of the product, the demographics of local buyers, and other environmental characteristics. While some attributes vary at the neighborhood scale (e.g. household income), others vary at larger scales (e.g., HOV access at the city level, government purchase incentives at the state or national level).

Consistent with the maturity of the US auto market, we assume that the market is saturated with a mature conventional product enjoying 100% market share. Consumers replacing their product make a binomial choice between the conventional (old) product o and a new product n. We formulate the model as a system of nonlinear differential equations in continuous time, using simulation to solve for the dynamics.

2.1 Consumer Choice

Consumers in neighborhood *x* currently using product $i \in \{o,n\}$ decide to purchase product $j \in \{o,n\}$ with market share σ_{ijx}. The share of consumers currently using product *i* who adopt product *j*, σ_{ijx}, follows a standard logit-choice structure, with the population-level affinity for product *j* as perceived by users of product *i* in neighborhood *x* a_{ijx}, divided by the sum over the affinity of the choice options (48):

$$\sigma_{ijx} = \frac{a_{ijx}}{\sum_{j'} a_{ijx}} \tag{1}$$

Here population-level affinity depends both on the intrinsic utility that consumers derive from product *j*, u_{jx}, and their willingness to consider the product in their purchase decision C_{ijx}., resulting from social influence processes:

$$a_{ijx} = C_{ijx} e^{u_{jx}} \tag{2}$$

The logit choice structure (Equations (1) and (2)) integrates the behavioral willingness to consider structure with utility-based rational discrete choice models. We show in the Supporting Information (S.1.1) that this formulation is fully consistent with rational choice models.

To facilitate estimation we make three simplifying assumptions about affinity across elements *i* and *j*. First, we assume that consideration of the established conventional product is constant and equal to one, because the conventional internal combustion technology is mature, stable, and familiar to all consumers. Second, we treat the conventional product *o* as an outside option with utility normalized to zero, therefore $a_{oox} = a_{nox} \equiv 1$, meaning we need only specify one utility term, u_x, for the alternative product, defined in relation to that of the outside option. Third, we assume that existing users of a product fully consider that product, therefore a_{nnx} does not depend on consideration: $a_{nnx} = e^{u_x}$. Thus, consideration C_{ijx} is endogenous only for current users of the conventional product (*i*=*o*) considering the new product (*j*=*n*). Hereafter, for simplicity, we refer to C_{onx} as C_x. Thus, $a_{onx} = C_x e^{u_x}$.

The mean utility of the new product in neighborhood x, u_x, comprises intrinsic product attributes I and environmental (demographic and market) characteristics E, as compared to the outside option:

$$u_x = \sum_p \beta_p I_{px} + \sum_q \beta_q E_{qx} \tag{3}$$

where both I and E contain elements, indexed p and q respectively, which may operate at specific geographic scales (e.g. ZIP code, county or state); the *β's* represent the sensitivity of utility to each product attribute or environmental characteristic.

2.2 Product Consideration

Novel durable goods are often expensive and complex, with multiple performance attributes, requiring consumers to learn about the product prior to adoption. Consumer consideration is the consequence of sustained exposure beyond mere awareness of the product's existence. We model consideration as a stock that accumulates over time as a result of repeated social exposure (16). The willingness of consumers in neighborhood x , currently using the conventional product, to consider the alternative, C_x, accumulates with social exposure to the product:

$$\frac{dC_x}{dt} = z_x\left(1 - C_x\right) \tag{4}$$

While the core consideration dynamics derive from Eq. 4 – the buildup of consideration through exposure, the model must account for the turnover rate of the installed base N_x because this affects the rate at which consumer consideration may build up, through (i) adopters switching from conventional to the alternative product, and (ii) alternative product adopters switching back to the conventional, bringing their consideration along with them. We capture the installed base turnover using a standard multiple-vintage cohort model (56). We provide this structure as well as the proper adjustment to preserve "conservation of consideration" in the Supporting Information (S.1.2).

In the tradition of marketing diffusion models (10), social exposure z_x comprises the influence of marketing and word-of-mouth from others who have adopted previously. Both marketing, $z_{m,lx}$, and word-of-mouth, $z_{s,lx}$, may operate at different geographic scales l. For example, a person in neighborhood x may experience global influence from public and media attention to a growing installed base of the new product, regional influence through exposure to the new product while traveling and working, or, local influence due to direct exposure to the new product in one's neighborhood, such as talking to a neighbor who owns the new product. Thus:

$$z_x = \sum_l \left(z_{m,lx} + z_{s,lx} \right) \tag{5}$$

Social exposure from advertising grows with advertising expenditure m_{lx} and with the effectiveness of advertising at each scale $e_{m,l}$. Hence: $z_{m,lx} = e_{m,l} m_{lx}$. Consistent with social contagion theories, social influence due to word-of-mouth from people in neighborhood x' influencing people in neighborhood x increases with: (i) the probability of contact with an adopter of the new product in x', $A_{x'}$ / N_x - with $A_{x'}$ and $N_{x'}$ being the total installed base of the alternative and all vehicles in x' respectively, because relatively more adopters in x' provide more opportunities for interactions with potential adopters in x; (ii) the relative intensity of social interactions between x' and x at scale l, $\rho_{lx'x}$; and (iii) the effectiveness of those interactions in generating consumer willingness to consider, $e_{s,l}$. Thus:

$$z_{s,lx'x} = \varepsilon_{s,l} \rho_{lx'x} \left(\frac{A_{x'}}{N_{x'}} \right) \tag{6}$$

with $z_{s,lx} = \sum_{x'} z_{s,lx'x}$. The model can accommodate various topologies of social influence between neighborhoods, including the perfect mixing assumption of classic diffusion models, or local influence only. Generally, we expect ρ to depend on the spatial and social distance between neighborhoods x' and x.

3 The Diffusion of the Toyota Prius

3.1 Experimental Design

We apply the model to the diffusion of the Toyota Prius in four US cities selected to capture variation in: (i) the extent to which local environmental conditions favor HEV adoption, as estimated using theoretical sampling (53) of all US Metropolitan Statistical Areas (MSAs); and (ii) the actual level of adoption observed. To score environmental favorability, we constructed a metric using attributes identified as influencing HEV adoption in prior research, including education, income, gasoline price, political preference (%), and vehicle miles traveled (5, 57-59). The selected cities are the San Francisco Bay Area (favorable environment / high adoption), Atlanta (favorable environment / low adoption), Phoenix (unfavorable environment / high adoption) and Dallas-Forth Worth (unfavorable environment / low adoption) (Fig. 3). (For details on the sampling process, and summary statistics for selected cities, see the Supporting Information S.2.)

We test four alternative models of social influence (Eq. 6), reflecting different hypotheses about the nature and geographic reach of social exposure for alternative fuel vehicles. We specify the models using the ZIP code as the geographic unit of analysis, the smallest level of aggregation for which new vehicle registrations are available. First, we consider an 'Aggregate' model that assumes a single geographical scale, with social influence generated uniformly from Prius vehicles in all ZIP codes. We define $\rho_{x'x} = N_{x'}/N \ \forall x$ so that social influence reduces to mean field or perfect mixing formulation, as in traditional diffusion models (9):

$$z_{s,xt} = \varepsilon_s^{ag}\left(\frac{A_t}{N}\right) \tag{7}$$

where $A_{x't}$ is the Prius installed base in ZIP code x' at time t, and $N = \sum_{x'} N_{x'}$ is the total vehicle ownership in the city, the relevant population for aggregate social exposure.

Next, we consider an 'Island' model, constraining social influence to interactions that occur within each local neighborhood (e.g. direct contact with vehicle owners on the street), with each ZIP code a social influence island. In the Island model, Eq. 6 is specified as:

$$z_{s,xt} = \varepsilon_s^{is}\left(\frac{A_{xt}}{N}\right) \tag{8}$$

Third, we consider a 'Central' model that includes influence across two geographic scales, combining the within-neighborhood influence of the Island model with a mean field approximation of all out-of-neighborhood interactions from every other neighborhood in the city:

$$z_{s,xt} = \varepsilon_s^{is}\left(\frac{A_{xt}}{N}\right) + \varepsilon_s^{ag}\left(\frac{\sum_{x'\neq x} A_{x't}}{\sum_{x'\neq x} N_{x'}}\right) \tag{9}$$

Finally, we test a 'Distance' model that also includes two geographic scales, combining the within-neighborhood influence of the Island model with a distance-dependent structure in which larger and spatially or socially nearby neighborhoods are more influential than smaller and more distant neighborhoods. Here $\rho_{x'x}$ captures the extent of influence from each neighborhood *x'* to each other neighborhood *x*, which need not be symmetric. Thus:

$$z_{s,xt} = \varepsilon_s^{is}\left(\frac{A_{xt}}{N}\right) + \varepsilon_s^{di}\rho_{x'x}\left(\frac{A_{x't}}{N_{x'}}\right) \tag{10}$$

These interactions arise largely as people drive across ZIP codes as they travel from home to work, school and other locations. We characterize these interactions using the Radiation model, a parameter-free model that allocates mobility among neighborhoods and has been shown to accurately describe real-world flows of travel, migration, communications and commodities (60, 61). The essence of the Radiation model, similar to the Gravity model, is that individuals are more likely to travel to locations that are superior to the next best opportunity, where a location's attractiveness increases with greater population, and decreases with increasing distance. In the Radiation model, the mixing share $\rho_{x'x}$ between locations *x'* and *x* depends on their populations, $P_{x'}$ and P_x respectively, and on the total population within a circle of radius $r_{x'x}$ centered at *x'*, not including P_x and $P_{x'}$, $S_{x'x}$ (61):

$$\rho_{x'x} = \frac{P_{x'}P_x}{\left(P_{x'} + S_{x'x}\right)\left(P_{x'} + P_x + S_{x'x}\right)} \tag{11}$$

The Supporting Information (S.3) provides evidence of the Radiation structure allowing the Distance model to be a representative intermediate model between the Aggregate and the Island models, and discusses tests with alternative formulations.

We model a range of environmental and attribute-related variables that influence the utility of the Prius, at various scales. We inlcud operating costs oc_t,, (a function gasoline prices and vehicle fuel economy) and net purchase price pp_t (including financial incentives for HEV adoption) as attributes that vary over time. At the ZIP code scale we include a range of socioeconomic and market heterogeneity variables including: educational attainment, race, age (three cohorts: 25-44; 45-64; >64), distance to the nearest Toyota dealership, and dependence on commuting by car. At the county level c_x, we include political preference, as a proxy for a preference towards environmental stewardship, a reasonable assumption given the strong correlation between political affiliation and beliefs about climate change and renewable energy (62). Finally, we use county-level fixed effects f_{c_x} to identify unobserved variation in local conditions. (Because Phoenix only has 2 counties we exclude political preference for this city.) Thus:

$$u_{xt} = \beta_1 oc_t + \beta_2 pp_{xt} + \beta_3 HOV_t + \beta_x E_x + \beta_4 pol_{c_x} + f_{c_x} + k \tag{12}$$

where E_x is the vector of zip-code level environmental characteristics and β_x the associated sensitivities to be estimated. The Prius constant k captures the influence of unobserved idiosyncratic characteristics of the Prius (such as performance, interior volume, aesthetics, and whether it confers social status) as well as the difference in the variety of makes, models and options available for the Prius compared to conventional vehicles.

3.2 Data Sources and Estimation

We compile data to estimate the model for the Prius from a variety of sources. We obtained quarterly sales data for the Prius. as well as total light vehicle sales (measured by new vehicle registrations) in each US ZIP code from January 2001 to December 2009 inclusive from R.L. Polk & Co., an automotive industry data provider. (The Supporting Information S.4 provides detailed information about the data, sources, and variables used). Of the more than 36,000 US ZIP codes that recorded vehicle sales between 2001 and 2009, the Prius had a median market share of 0.24% of cumulative light vehicle sales. The Prius achieved more than 1% market share of light vehicle sales in 3,764 ZIP codes, and more than 5% market share in 81 ZIP codes, mostly in California.

We calculate state-average quarterly retail gasoline prices from US Energy Information Administration data. Governments have offered various incentives to promote consumer adoption of HEVs. At the federal scale, HEV incentives included a $2,000 tax deduction from 2004-2005, and a tax credit of up to $3,150 from 2006, available for the first 60,000 hybrid vehicles sold per manufacturer. The only state government incentive available in the cities we study was to allow single occupant use of hybrid vehicles in High Occupancy Vehicle (HOV) lanes. In California, a total of 85,000 decals were made available for buyers of a range of hybrid vehicle models, a benefit valued at $4,000 over the life of the vehicle (63). In Arizona, 10,000 HOV plates were made available for buyers of the Toyota Prius, Honda Insight and Honda Civic hybrids. Georgia and Texas did not implement HOV lane incentives for hybrid vehicles. Data obtained from Kantar Media show that Toyota spent an estimated $276 million on Prius-specific advertising between 2000 and 2009, of which $239 million was spent on national media including television, internet and print media, with the rest allocated regionally. We use data from the year 2000 decennial census administered by the US Census Bureau to capture socio-economic factors including household income, educational attainment, race, age and the population commuting to work by car. In addition, we obtained the address of every Toyota dealership in the United States from the Toyota website to measure the convenience with which a customer could purchase a Prius. Finally, we use data on voting patterns from the 2000 US Presidential election as a proxy for a preference towards environmental stewardship.

We estimate the models for January 2000 to December 2009 inclusive. We limit estimation to the period prior to 2010 when a number of structural changes to the Prius market occurred, including a highly publicized safety recall, major supply disruptions because of the Tsunami and Fukushima disaster in Japan and the introduction of additional Prius body styles. We model sales of the Prius as a binomial choice between the Prius and a representative conventional gasoline vehicle in the Prius market segment. Doing so is reasonable because consumers tend to choose vehicles within market segments each containing a limited number of relatively similar makes, models and body styles, e.g., compacts, mid-size sedans, and SUVs (64, 65). We use the US EPA segment definitions to define the segment in which the Prius competes, selecting a comparable make and model to represent the attributes of gasoline vehicles available in that segment. The first generation Prius (2000-2003) was classified a compact car, comparable to the Toyota Matrix. After a major redesign, the EPA classified the second and third generation Prius (2004 onwards) as a mid-sized car, comparable to the Toyota Camry.

We estimate the models using MLE for $d = \Sigma_{xt} d_{xt}$ adoption decisions between conventional vehicles and the Prius, where d_{xt} is the total number of vehicle sales in ZIP code x in quarter t. We specify the likelihood function as a function of the estimated probability of Prius sales, and the actual observation of Prius and non-Prius adoptions, in each ZIP code-quarter (Supporting Information S.5). We use Markov Chain Monte Carlo (MCMC) simulation to estimate parameter confidence intervals (66). MCMC is particularly suited for estimating confidence intervals for non-linear dynamic models (67, 68).

4 Results

We estimate all four alternative social influence models for each of the four selected cities (Table 1 & 2). The 16 resulting models all include the same utility-related independent variables. We report model parameters and ZIP code-average summary statistics, including the breakdown of total socialization in each ZIP code, and, to understand biases in estimations, Theil statistics, which decompose residual differences between the model and the data into three components: bias (U^m), unequal variation (U^s) and unequal covariation (U^c).

Model 1 (Aggregate) is a classic diffusion model with uniform social exposure across all ZIP codes in the city. The aggregate model serves as a null hypothesis in which any non-random heterogeneity in adoption across ZIP codes is necessarily attributed to variations in local conditions rather than social influence. Across all 4 cities both advertising and word-of-mouth are statistically significant sources of social exposure to the Prius, with aggregate word-of-mouth accounting for between 40% and 77% of total socialization. The estimated utility parameters, which we discuss in further detail below, are generally consistent with expectations.

While the Aggregate model captures variation in local conditions across ZIP codes, the model is structurally misspecified in terms of social exposure processes because it assumes social influence, and thus willingness to consider, are uniform across ZIP codes. As a result, the Aggregate model is forced to explain all spatial-temporal variability in adoption as resulting from heterogeneity in product utility across ZIP codes, thus suppressing the explanatory power of product consideration. To illustrate, average ZIP code-level consideration in the Aggregate models ("Av Consideration", $C=\Sigma N_x C_x/N$ for quarter 4 of 2009) ranges between *0.002* and *0.005* in our four cities. By contrast, a survey by Maritz Research (69) suggests that 22% of US drivers considered themselves 'very familiar' with gasoline hybrid electric vehicles. Further, whereas we expect k to be negative given that it captures not only idiosyncratic preferences but also the wide variety of makes and models of conventional vehicles available, we find the Prius constant estimated here to be positive and unrealistically large for all cities ($k = 1.178$ *to* 4.221). A value of k = 1.178 implies the Prius could attain, under full consideration, 76% market share in the segment in which it competes, far greater than that of the best selling vehicle models in the United States.

We therefore relax the strong assumption of uniform social influence. First we analyze the Island model, allowing consideration to accumulate differently across ZIP codes, but hypothesizing that social influence from word-of-mouth is limited to local interactions between adopters and potential adopters within each individual ZIP code. Both advertising and within-ZIP word-of-mouth are statistically significant sources of social exposure in each city. As expected, within-ZIP word-of-mouth accounts for larger shares of total social exposure in the high adoption cities (75.6% in San Francisco and 89.1% in Phoenix) compared with the low adoption cities (60.3% in Atlanta and 63.5% in Dallas-Fort Worth).

The spatial disaggregation of social influence to the neighborhood scale in the Island model results in a substantial improvement in model performance compared to the Aggregate model, as reflected in a statistically significant improvement in log-likelihood in all four cities. The Island model leads to different estimates of consideration and diffusion across ZIP codes, and yields a plausible estimate of the market potential of the Prius (determined by the Prius-specific constant k). For example, applied to San Francisco, the Island model finds that average ZIP-code Prius consideration reaches 0.359 in the fourth quarter of 2009, and k is negative and statistically significant (k = -0.831), consistent with the conventional product being available in a range of makes, models and body styles.

Previous studies have described the difficulty in identifying social exposure parameters separately from the market size when relying on data early in the diffusion lifecycle (9, 70, 71). The Island model is not subject to this problem because the buildup of consideration is spatially disaggregated. Correspondingly, the model, with willingness to consider building up over time at the ZIP code level, captures their distinct sales trends more effectively, reflected in lower bias (U^m), and, in the case of the high adoption cities, lower unequal variance, (U^s), implying the model better captures the mean of the data. Together, the Island models provide evidence that the observed patterns of Prius adoption are explained in part by social influence occurring at the neighborhood rather than aggregate scale.

Consistent with numerous previous studies of consumer choice in the automotive market, we find a negative effect of operating costs on utility across all cities: higher gasoline prices and operating costs decrease vehicle utility, benefiting the more fuel-efficient Prius. We find the effect of vehicle purchase price to be negative and statistically significant in Atlanta and Dallas-Fort Worth, as expected, but positive and statistically significant in the Bay Area and Phoenix. Prices are endogenous and dynamic: dealers are able to charge more for vehicles when demand is high. Lengthy and persistent waitlists existed to purchase a Prius in the mid-2000s (59), and these waitlists appear to have been longer in Toyota's western region (California, Oregon, Washington, Nevada and Arizona), suggesting that excess demand and hence prices were higher in the high adoption cities (72). The positive price coefficient for the Bay Area and Phoenix is therefore likely to reflect the endogenous response of prices to demand in these cities.

The influences of socio-economic variables affecting utility through local conditions are generally as expected. The utility of the Prius is higher in ZIP codes with higher educational attainment, less non-

Caucasian racial diversity, and a more middle-aged population. Evidence about the influence of political preferences is mixed. A higher fraction of Democratic voters has a positive effect on Prius utility in Atlanta, as expected. Contrary to conventional wisdom, the fraction of Democratic voters in the 2000 Presidential election has a negative and statistically significant effect on utility in Dallas-Fort Worth and the Bay Area. The explanation is unclear: either those voting Republican in these regions were more likely to buy a Prius than those who voted Democratic, or party choice in that election does not provide sufficient information on the public's environmental concerns or other values that bear on the attractiveness of the Prius.

Prius utility is higher in ZIP codes further away from Toyota dealerships in all cities except Dallas-Fort Worth, which initially seems counter-intuitive. However, car dealerships are usually strategically located in high traffic areas, which are typically not the neighborhoods where affluent Prius buyers live, suggesting that the positive coefficient is the result of collinearity between Toyota dealership locations and Prius buyer demographics. Finally, we find a strongly positive effect of HOV lane access incentives on Prius utility in San Francisco and Phoenix.

In the Island models, the utility parameters and fixed effects (Supplementary Information S.6) are in general considerably smaller in magnitude than in the Aggregate models, and some change signs to be consistent with expectations. These results suggest that spatial disaggregation of social influence and product consideration is important in explaining the observed heterogeneity in spatio-temporal adoption.

However, the Aggregate and Island models discussed so far represent extremes in terms of social influence, with uniform social influence across a city, and neighborhood-only social influence respectively. Next we consider the Central model, which combines the within-ZIP word-of-mouth of the Island model with mean field social influence from all other ZIP codes in the city. The inclusion of mean field out-of-ZIP social influence results in a highly statistically significant improvement in log-likelihood compared to the Island model in all four cities (the test statistic with lowest confidence is for the Bay Area, $G \sim \chi_{df=1} = 18$, p = 2.2e-5). In the Central model the coefficient for the mean field out-of-ZIP social influence is positive and statistically significant in all 4 cities. The contribution of mean field social influence is relatively small compared with within-ZIP social influence, accounting for only 5.8% of total Prius socialization in the Bay Area, and between 15.4-25.4% of total Prius socialization in the other cities, suggesting that local exposure to the Prius in one's home ZIP code is particularly important in the build up of consideration.

Finally, we relax the assumption of mean-field out-of-ZIP social influence. In the Distance model, social influence from all other city ZIP codes is weighted according to the radiation model, in which adoption decisions are influenced more strongly by the Prius stock in other ZIP codes that have larger populations and are closer—large and near neighborhoods are more likely to generate exposure to the Prius than those smaller and farther away. The Distance model yields a statistically significant improvement in log-likelihood compared with the Island model in all cities except for Dallas Fort-Worth (for the Bay Area, $G \sim \chi_{df=1} = 72$, p <0.00001). The coefficient for out-of-ZIP social influence is positive and statistically significant in all 4 cities.

Taken together, the results of the Central and Distance models provide strong support for the hypothesis that social influence occurs at multiple geographic scales in the diffusion of the Toyota Prius, yielding positive and statistically significant coefficients for regional social influence in all four cities. Further, compared with the Island model, the improvement in log-likelihood is statistically significant in all cases except for the Distance model in Dallas Fort-Worth. We cannot adjudicate which of these two regional influence models – Central or Distance – is superior using a LR test, as the models are not nested. Using the Bayesian Information Criterion (BIC) (73) to compare the models suggests that the Distance model is superior in the Bay Area, meaning that larger and closer ZIP codes are relatively more important, while the Central model performs better in the other three cities. There is reason to place relatively more weight on results of the Bay Area, having substantially higher Prius adoption, and fewer non-zero Prius adoption instances, than the other three cities (Supporting Information S2.3). However, differences in the relative performance of the Central and Distance models across the cities may also point to variation in social influence structures across the cities, for example resulting from distinct travel patterns or social interactions.

5 Discussion

The clustered nature of spatio-temporal Prius adoption in the United States is intriguing, because two compelling explanations exist. Consistent with rational consumer choice theory, clustering could result from heterogeneity in local conditions (such as fuel prices), or in consumer preferences for vehicle types (such as compacts vs. SUVs and pickup trucks) arising from differences in education, political affiliation, and other socio-demographic factors. Alternatively, clustering could arise as heterogeneity in local conditions is amplified by processes of social contagion such as word-of-mouth and direct exposure to the product, processes central in the marketing diffusion literature. At the population level, our results suggest that social influence plays an important role in explaining the clustered patterns of diffusion observed. At the level of the individual adopter, our findings suggest a complex social influence process, with the buildup of consideration requiring reinforcement from multiple sources. The dominant role of local social influence suggests that direct exposure to the product—observing a Prius in use or speaking to a Prius owner in person—is most important, consistent with the expensive, culturally and technologically complex and durable nature of the Prius. The relatively modest effect of regional social influence that we find is consistent with the hypothesis that repeated, direct exposure is important for products that are novel, complex, durable and expensive.

Our analysis highlights the importance of jointly representing local conditions and social influence at different scales to explain spatio-temporal diffusion. Models that capture consumer adoption of new products typically involve either utility-based factors related to individual preference and environmental conditions or diffusion models capturing social influence processes related to word of mouth and exposure to the product. Capturing either in isolation may lead to structural misspecification of diffusion models resulting in biased estimates of product attribute elasticities and socialization parameters.

The presence of both local and regional social influence implies that consumer adoption decisions are temporally and spatially interdependent, which has important strategic implications. Policies to promote the adoption of unfamiliar new technologies generally, and eco-friendly technologies needed to achieve important environmental goals such as reductions in greenhouse gas emissions specifically, typically focus on incentives designed to increase affordability. Such policies have worked in some areas but not in others, resulting in slow, uneven adoption that limits the environmental benefits. The results suggest broad uptake of these technologies also requires policies that strengthen the social processes that condition local exposure to the product and build the willingness of consumers to consider adoption. If clustered adoption were explained by differences in demographics and local conditions alone, product launch strategies could target specific demographic profiles—if preferences were observable. However, the interaction of local conditions and spatial social influence implies that interventions to accelerate adoption will be most cost-effective targeting neighborhoods where social influence can amplify favorable local conditions, and enable the subsequent spread to nearby neighborhoods. Targeting these early adopters is appealing not only because their adoption threshold is low, but because they continue to generate social exposure opportunities leading to further adoption in their own neighborhood and nearby.

While our analysis captures a wide range of factors with the potential to influence HEV adoption, we recognize that unobserved factors, dynamic or latent, could also have influenced the appeal of HEVs. For example, alternative explanations for growth in Prius sales over time could involve increasing concern about anthropogenic climate change and sustainability issues. This seem unlikely, because belief in climate change in the US actually decreased over the time period we study (62). We also recognize the existence of lengthy waitlists to purchase a Prius through the mid-2000s, indicating demand for the Prius exceeded the available supply (20). However, we do not expect waitlists to explain spatial variation in Prius adoption within each city because buyers can shop around multiple Toyota dealerships, and Toyota dealers trade vehicles between dealerships to manage inventory; such behaviors will tend to equalize wait lists within a metropolitan area. Finally, our analysis does not capture how interactions with distant regions outside the city, such as travel and telephone calls, may influence the diffusion process. A very high degree of correlation exists between national Prius sales and aggregate Prius sales in each of the 4 cities we study ($r \geq 0.94$), and we are not able to isolate national-level effects with our design. However, our finding that social exposure from nearby sources is more powerful than those from distant but within-city sources suggests that still more distant word of mouth, which for automobiles precludes exposure to the actual vehicle, is not likely to be significant.

We expect that the nature of social influence varies greatly across product types. For simple products, traditional advertising on television, radio and in print media is sufficient to build awareness of new products. For others, single communication channels may provide critical opportunities for information exchange. However, for complex products that challenge social norms, as is the case with alternative fuel vehicles, the buildup of consumer acceptance requires time and exposure through multiple channels of social influence. For such products, our approach allows the representation of a wide range of assumptions about how social influence varies with factors including distance, geography and socio-demographic attributes.

The insights we gain from the Prius case extend to other culturally complex and durable products and practices, including many sustainability-oriented innovations that challenge deeply held norms and entrenched socio-technical systems. Understanding the processes that govern spatiotemporal diffusion requires models that distinguish between market heterogeneities and social influence, at multiple spatial scales. Strategies and policies to accelerate adoption must exploit social influence processes to build acceptance and adoption if the potential benefits of innovations such as electric vehicles, car sharing, and energy-efficient homes are to be realized. Policies that provide opportunities for people to experience the novel features of these innovations first-hand, and to share that knowledge with those around them, are essential for successful market formation.

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7 Tables and Figures

Table 1: Results - High Adoption Cities

City	San Francisco Bay Area				Phoenix			
Social Influence Structure	Aggregate	Island	Central	Distance	Aggregate	Island	Central	Distance
Effectiveness of Advertising ε^{m}	1.4E-4 ‡	0.010 ‡	0.009 ‡	0.008 ‡	3.6E-5 ‡	0.005 ‡	0.004 ‡	0.004 ‡
Aggregate WoM ε^{ag}	0.045 ‡	-	-	-	0.081 ‡	-	-	-
Within-ZIP WoM ε^{is}	-	7.031 ‡	6.108 ‡	4.705 ‡	-	38.336 ‡	31.934 ‡	36.463 ‡
Out-of-ZIP WoM – Mean Field ε^{mf}	-	-	0.349 ‡	-	-	-	5.263 ‡	-
Out-of-ZIP WoM – Distance ε^{di}	-	-	-	0.808 ‡	-	-	-	3.639 ‡
Constant (Prius)	1.786 ‡	-0.831 ‡	-0.831 ‡	-0.343 ‡	1.596 ‡	-3.119 ‡	-3.061 ‡	-3.002 ‡
Operating Cost	-0.166 ‡	-0.130 ‡	-0.127 ‡	-0.123 ‡	-0.073 ‡	-0.051 ‡	-0.031 ‡	-0.047 ‡
Purchase Price	0.342 ‡	0.298 ‡	0.307 ‡	0.309 ‡	0.323 ‡	0.375 ‡	0.428 ‡	0.409 ‡
Educational Attainment	1.799 ‡	0.803 ‡	0.854 ‡	0.812 ‡	0.193	0.229 †	0.207 ‡	0.265 ‡
Political Preference	0.201 ‡	-1.027 ‡	-0.992 ‡	-1.416 ‡	-	-	-	-
Race	-0.310 ‡	-0.086 ‡	-0.097 ‡	-0.115 ‡	-1.232 ‡	-0.149 ‡	-0.411 ‡	-0.125 ‡
Age 25-44	0.095	-0.143 ‡	-0.103	-0.115 †	4.648 ‡	1.418 ‡	1.951 ‡	1.055 ‡
Age 45-64	2.756 ‡	1.461 ‡	1.511 ‡	1.702 ‡	0.518 †	0.418 *	0.386 ‡	0.395 †
Age 64+	0.272 †	-0.254 ‡	-0.206 †	-0.286 ‡	2.128 ‡	0.457 †	0.627 ‡	0.349 ‡
Dealership Distance	0.002 †	0.003 ‡	0.003 ‡	0.004 ‡	0.014 ‡	0.007 ‡	0.008 ‡	0.008 ‡
Car Commuting	-1.051 ‡	-0.595 ‡	-0.604 ‡	-0.520 ‡	-0.417 ‡	0.411 ‡	0.331 ‡	0.432 ‡
HOV Lane Access (Dummy)	0.649 ‡	0.588 ‡	0.593 ‡	0.602 ‡	0.667 ‡	0.548 ‡	0.537 ‡	0.533 ‡
County Fixed Effects	Yes (8)				Yes (1)			
Log-Likelihood	-183221	-182164	-182155	-182128	-48736.2	-48503.6	-48463	-48499.5
Consideration	0.005	0.359	0.340	0.295	0.003	0.673	0.666	0.678
R^2	0.613	0.602	0.604	0.605	0.587	0.568	0.573	0.568
Socialization % - Marketing	32.2	24.4	23.2	21.4	23.3	10.9	7.6	8.5
Socialization % - Aggregate WoM	67.7	-	-	-	76.7	-	-	-
Socialization % - Within-ZIP WoM	-	75.6	71.0	63.7	-	89.1	77.1	81.4
Socialization % - Out-of-ZIP WoM	-	-	5.8	14.9	-	-	15.4	10.2
Theil Bias Fr (*Um*)	0.132	0.062	0.066	0.066	0.085	0.045	0.047	0.044
Theil Unequal Variance Fr (*Us*)	0.131	0.123	0.120	0.119	0.215	0.161	0.168	0.153
Theil Unequal Covariance Fr (*Uc*)	0.737	0.816	0.815	0.814	0.698	0.793	0.783	0.802

‡ significant at $p < 0.01$; † significant at $p < 0.05$; * significant and $p < 0.1$

Table 2: Results - Low Adoption Cities

City	Atlanta				Dallas-Fort Worth			
Social Influence Structure	Aggregate	Island	Central	Distance	Aggregate	Island	Central	Distance
Effectiveness of Advertising ε^{m}	6.0E-5 ‡	0.006 ‡	0.004 ‡	0.004 ‡	5.0E-5 ‡	0.016 ‡	0.014 ‡	0.016 ‡
Aggregate WoM ε^{ag}	0.106 ‡	-	-	-	0.039 ‡	-	-	-
Within-ZIP WoM ε^{is}	-	14.226 ‡	12.107 ‡	9.738 ‡	-	41.598 ‡	38.037 ‡	41.792 ‡
Out-of-ZIP WoM – Mean Field ε^{mf}	-	-	4.812 ‡	-	-	-	14.470 ‡	-
Out-of-ZIP WoM – Distance ε^{di}	-	-	-	2.051 ‡	-	-	-	3.842 †
Constant (Prius)	4.221 ‡	-1.062 ‡	-1.053 ‡	-1.077 ‡	1.178 ‡	-2.667 ‡	-2.584 ‡	-2.788 ‡
Operating Cost	-0.031 ‡	-0.026 ‡	0.011	-0.017 †	-0.053 ‡	-0.044 ‡	-0.022 *	-0.045 ‡
Purchase Price	-0.257 ‡	-0.217 ‡	-0.157 ‡	-0.208 ‡	-0.058 ‡	-0.066 ‡	-0.020	-0.046 †
Educational Attainment	-0.148 ‡	-0.424 ‡	-0.401 ‡	-0.582 ‡	0.461 ‡	0.234 ‡	0.391 ‡	0.242 ‡
Political Preference	-1.865 ‡	0.161 *	0.813 ‡	0.423	6.085 ‡	-0.960 ‡	-0.779 ‡	-0.295
Race	-0.531 ‡	-0.387 ‡	-0.430 ‡	-0.431 ‡	-0.395 ‡	-0.450 ‡	-0.382 ‡	-0.462 ‡
Age 25-44	-0.851 ‡	-0.372 ‡	-0.496 ‡	-0.237 *	0.647 ‡	0.662 ‡	0.375 ‡	0.524 ‡
Age 45-64	2.375 ‡	0.990 ‡	1.234 ‡	1.396 ‡	1.423 ‡	0.997 ‡	1.119 ‡	0.998 ‡
Age 64+	-1.527 ‡	-0.659 ‡	-0.819 ‡	-0.666 †	2.580 ‡	2.051 ‡	1.703 ‡	1.691 ‡
Dealership Distance	0.012 ‡	0.005 †	0.006 ‡	0.005 †	-0.006 ‡	-0.004 ‡	-0.004 ‡	-0.004 †
Car Commuting	-2.369 ‡	-1.244 ‡	-1.459 ‡	-1.195 ‡	-0.483 ‡	-0.222 ‡	-0.460 ‡	-0.266 †
HOV Lane Access (Dummy)	-	-	-	-	-	-	-	-
County Fixed Effects	Yes (19)				Yes (12)			
Log-Likelihood	-34916.7	-34826.6	-34806.6	-34819.6	-45467.6	-45416.4	-45407.7	-45415.9
Consideration	0.004	0.292	0.305	0.239	0.002	0.596	0.651	0.611
R^2	0.340	0.329	0.332	0.332	0.342	0.338	0.342	0.337
Socialization % - Marketing	40.6	39.7	25.5	37.4	59.7	36.5	25.7	33.2
Socialization % - Aggregate WoM	59.4	-	-	-	40.3	-	-	
Socialization % - Within-ZIP WoM	-	60.3	49.0	53.7	-	63.5	50.5	59.7
Socialization % - Out-of-ZIP WoM	-	-	25.4	8.9	-	-	23.8	7.1
Theil Bias Fr (*Um*)	0.074	0.049	0.053	0.052	0.081	0.064	0.071	0.064
Theil Unequal Variance Fr (*Us*)	0.257	0.259	0.242	0.251	0.258	0.266	0.247	0.258
Theil Unequal Covariance Fr (*Uc*)	0.669	0.691	0.704	0.696	0.661	0.670	0.682	0.677

‡ significant at $p < 0.01$; † significant at $p < 0.05$; * significant and $p < 0.1$

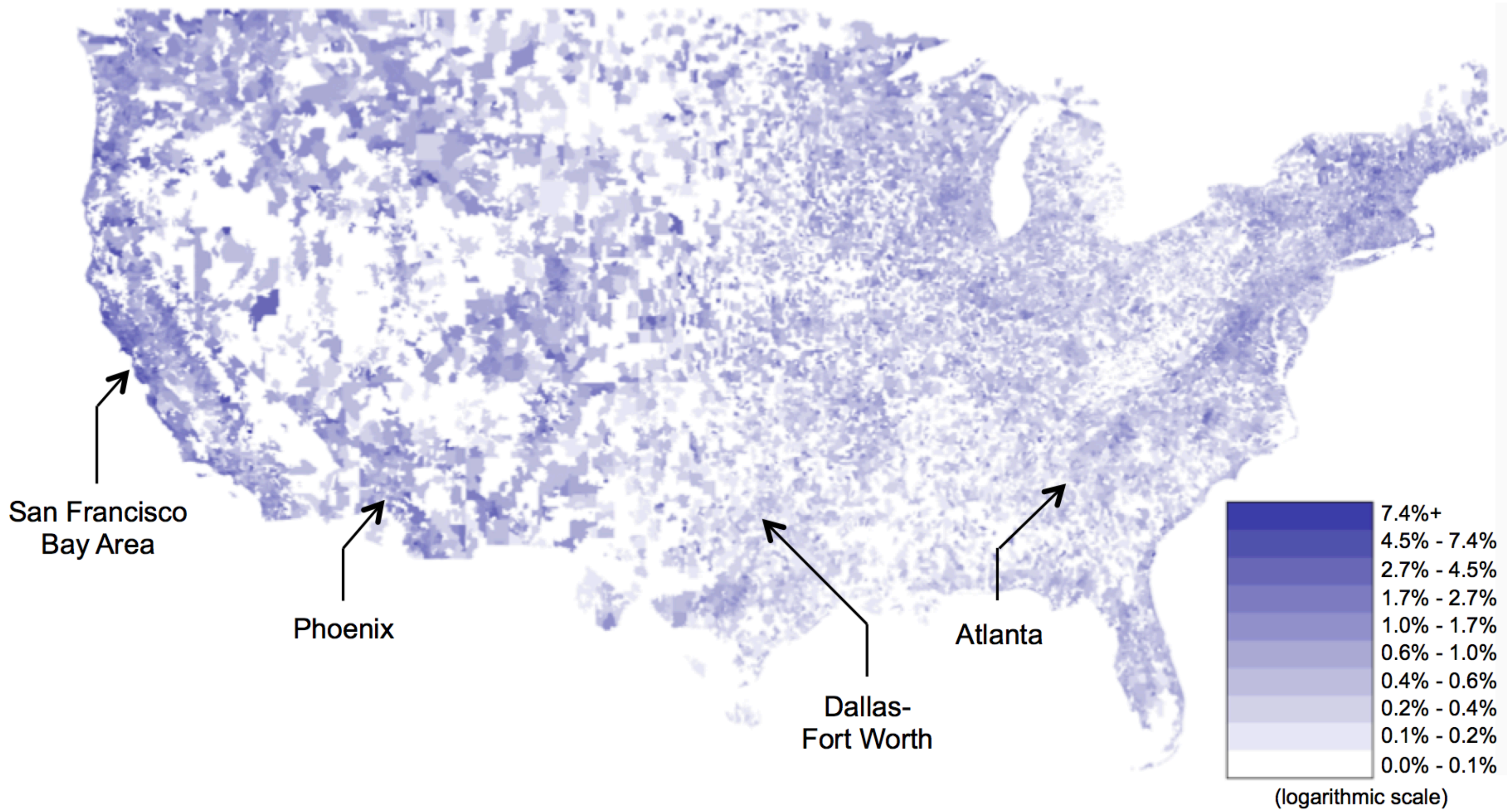

Fig.1. Prius market share by ZIP code shows clustering in regions including the West Coast, New England and around Washington DC.

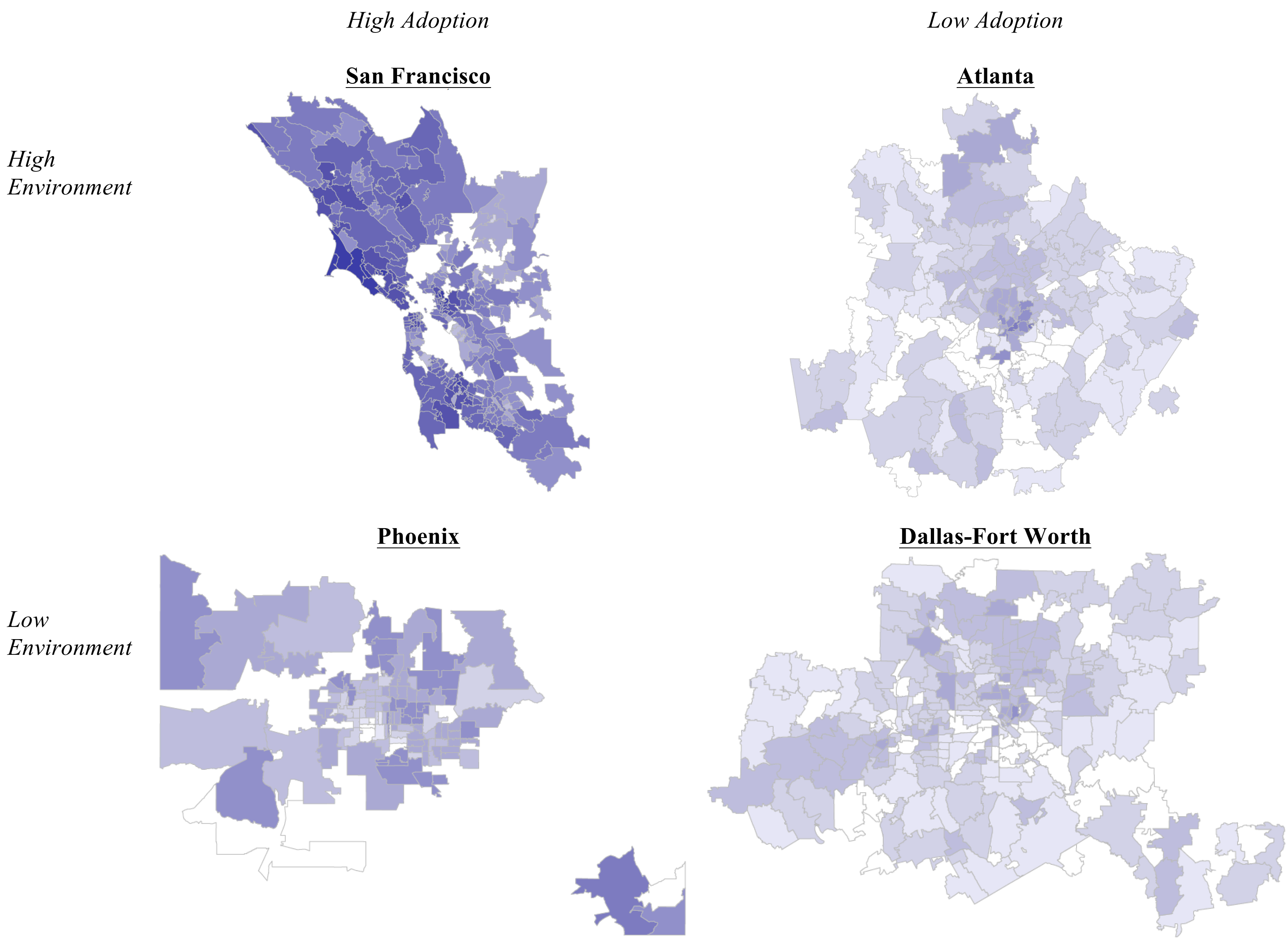

Fig.2. ZIP code level Prius market share 2000-2009 for our strategically selected cities.