Peer Pressure Enables Actuation of Mobility Lifestyles

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This paper explores the utility of peer pressure as an actionable mechanism to induce socially responsible and environmentally-conscious mobility habits. We adopt a two-stage game theoretic model of peer pressure to investigate feedback between social, geographic, and temporal dimensions of agent choices in a hyper-realistic micro-simulation of travel. The results show that peer pressure helps achieving desirable equilibrium properties while reducing congestion and emissions due to sustained mode shift. With a way to initiate the required social norming and a proper concern for privacy and ethics, these cost-effective mechanisms may soon begin to find use in improving community welfare.

Key words: Games on social networks, data mining, machine-learning, microsimulation, activity-based models, network interventions, climate change policy, mode shift, social welfare maximization, peer-pressure.

1. Introduction

Surging interest and political acceptance of behavioral interventions or nudges have created novel opportunities for transportation planners to strategically structure mobility choice architectures that actuate and stabilize environmentally-beneficial mobility lifestyle changes (Leonard et al. 2008, Avineri 2012). Voluntary travel behavior change and personal travel planning have been in use since the 1980s to persuade commuters to engage in pro-environmental and pro-social travel behaviors (Fujii and Taniguchi 2006). More recently, ubiquitous, networked computing technologies and social media channels have provided additional outlets to motivate and sustain behavior change (Jariyasunant et al. 2015, Gaker et al. 2010, 2011). While empirical and theoretical evidence suggests social norms and personalized feedback can reinforce positive attitudes towards sustainable mode choice (Brög et al. 2009), little work has been done to rigorously and independently evaluate the costs and benefits of novel behavioral policy alternatives (te Brömmelstroet 2014, Bonsall 2009).

Simulations of cyber-social influence on travel decision-making may help transit agencies quantitatively and transparently justify to stakeholders programs intended to incentivize peer-to-peer influence as a means of encouraging socially cooperative modality lifestyles. Herein, we adapt a two-stage game theoretic model of peer pressure inspired by (Mani et al. 2013) to investigate how feedback between social, geographic, and temporal dimensions in agent-based simulations of travel
can motivate pro-environmental transportation decisions. This work extends related research on
joint-decision making as well as the cost-benefit analysis of policy incentives to internalize the envi-
ronmental externalities of transportation \cite{Illenberger2012, DubernetAxhausen2013, Axhausen2007, AgarwalKickhofer2015, KaddouraKroeger2015, KickhoferKern2014}. The
software implementation of our model is built on top of the open-source microsimulation software,
MATSim, which was chosen for its compatibility with behavioral choice theories, modularity, and
ability to handle large heterogeneous populations of agents \cite{Hornietal2016}.

We verify our system on a scenario situated in the San Francisco Bay Area in California. By
monetizing reductions in emission and congestion externalities, we evaluate the effect of potential
policy instruments intended to motivate agents to influence their peers to use public transit instead
of commuting to work alone. While experimental results are focused on public transportation as
an alternative mode, the game-theoretic setting and experimental simulation developed by this
work covers a wide class of situations characterized by a high price of anarchy \cite{KoutsoupiasPapadimitriou2009} where selfish behaviors (such as driving alone) curtail system performance.

2. Related Work

By definition, common pool resources are freely-available and ungoverned \cite{Ostrom2010}. The
tragedy of the commons may occur when a common pool resource is depleted to the extent that each
additional unit of consumption reduces the value of the resource for the entire society \cite{Hardin1968}. The tragedy of the commons has been frequently studied in the economics, control, and distributed
artificial intelligence communities using game theoretic models representing agent decision-making
related to the overuse of telecommunication, transportation, wildlife, and global climate resources
the transportation setting, commons constraint problems occur when users of a road network seek
to maximize their expected individual utility without regard for capacity limitations \cite{SahaSen2003}. The resulting costs of congestion and pollution are felt by everyone.

An externality is defined as an experienced cost or benefit due to the failure of a rational economic
actor to take into account the consequences of their behavior on others \cite{Verhoef1994, Rothengatter1994}. Externalities can be characterized as positive or negative depending on whether they benefit
or harm parties external to the action in question.

The scope of transportation externalities may vary from local to global. For example, the noise
pollution from a loud motorcycle engine can irritate people in the immediate vicinity of the vehicle.
In contrast, \( \text{CO}_2 \) emissions from fossil-fuel powered automobile exhaust contribute to global climate
change, which has a more diffuse social cost. External costs need not be directly monetary in nature.
The increase in travel delays caused by an additional driver on the road network affects commuters
in accordance with the value that they place on time \cite{Small2012}.
Making individuals aware of the effects of their decisions on others in order to reduce externalities is known as **internalization**. **Pigouvian mechanisms** are market-based approaches that attempt to internalize externalities by taxing goods resulting in net disbenefits or subsidising goods that result in net benefits ([Pigou 1920](#)). However, as the scope of external effects increases, Pigouvian schemes become more politically contentious, as attributing effects to their sources becomes less precise. Pigouvian mechanisms also fail to take advantage of the social effects that often shape individual behavior and preferences.

Game theoretic models of externalities assume that, at equilibrium, individuals lack the incentive to take actions that improve social welfare if they believe that others will profit from their efforts without making a similar sacrifice in utility. However, in many cities, a growing concern over the contribution of fossil fuel emissions to climate change and increasing access to low-cost, alternative-energy transportation modes, has resulted in commuters switching to public transit, electric vehicles, and ridesharing services at rising rates ([Biel and Thøgersen 2007](#), [SFCTA 2010](#)). For example, recent work studying automobile purchase decisions shows to what extent adoption of a new technology (such as electric vehicles) is driven by the spread of attitudes and behaviors (e.g., pro-environmental mode choice) as they become social norms ([Gaker et al. 2011](#)).

Traditional consequentialist views of travel behavior have failed to explain these preferences, inspiring modern studies of transportation behavior to investigate bounded rationality, observer bias, and, increasingly, the impact of social influence on human reasoning ([Grabowicz et al. 2014](#), [Verplanken et al. 2008](#), [Axhausen 2007](#), [Scott 2004](#)). Complicating claims of causality made by these experiments is the difficulty in accounting for endogeneity in explanatory variables ([Dugundji and Walker 2005](#)). Distinguishing social influence from homophily, which is defined as the tendency for individuals with similar characteristics and behaviors to form clusters in social networks is currently a growing area of research and debate.\(^1\)

In contrast to the passive processes governing diffusion of social influence, individuals can, at some cost in utility to themselves, actively influence each others’ choices through **peer pressure** ([Pentland and Reid 2013](#), [Calvó-Armengol and Jackson 2010](#), [Mani et al. 2013](#)). In particular, when one person’s choices result in visible negative externalities for his community, his peers may collectively decide to persuade him to make decisions that internalize the consequences of his actions; thus incrementally reducing local perception of the "free-rider" problem ([Lazaer and Kandel 1992](#)).

While pressure is always costly to the pressuring party, it can either lower or raise the cost of pressured agents’ action depending on whether it is positive or negative, respectively. A group of friends protesting a mutual acquaintance’s decision to buy a fuel-inefficient SUV can be seen as

\(^1\) See [Christakis and Fowler 2013](#) and [Shalizi and Thomas 2011](#) for a recent exploration of the identification problem in the econometric analysis of diffusive processes in social networks, as first characterized in ([Manski 1993](#)).
negative peer pressure. On the other hand, lending a friend a bicycle for "Bike to Work" day can be seen as positive peer pressure.

Mani et al. (2013) recently developed a two-stage game theoretic mechanism that models localizing the perception of global externalities within social networks in order to drive peer pressure-induced cooperation. In this work, we adapt a similar game theoretic mechanism to a transportation setting wherein we show that peer pressure helps to internalize global externalities arising from the use of personal vehicles on road networks. Experimental evidence from validation studies based on the theory developed in Mani et al. (2013) suggests that rewarding individuals with a low cost of peer pressure amplifies the effects of subsidies by taking advantage of inherent social capital. These effects were shown to be more cost-effective than comparable Pigouvian internalization mechanisms.

The model of peer pressure presented herein is implemented within a framework of agent-based microsimulation of mobility based on activity-based travel demand. Activity-based travel demand models (ABMs) primarily differ from traditional travel demand models in that they take into account travelers’ daily schedules and activity priorities (Castiglione et al. 2014). Agent-based microsimulations execute the planned activities and transportation choices of many software agents interacting on a virtual representation of physical road networks. The spatiotemporal granularity of human environments and interpersonal dynamics represented by these simulations permits the resolution of feedback loops and constraints that operate between trips purposes, travel mode alternative availability, and infrastructure status. Individual decision-making may also be made dependent on demographics such as household member composition, income, and ethnicity (Vij and Walker 2013).

Related research efforts have incorporated the effect of social influence on transportation, particularly in the sphere of joint decision-making (Hackney and Axhausen 2006). Studies designed to employ synthetic social networks of travelers as well as simulate joint activity choice, vehicle sharing, and household-level coordination of plans have been implemented (Dubernet and Axhausen 2013, Illenberger 2012). While our work is similar in that we extend a microsimulation with a social network of traveling agents, the scenario presented herein does not involve joint decision-making by agents during the course of plan evaluation.

As a tool for economic analysis of policy interventions, the agent-based approach has proven to be adaptable to modeling the effects of emissions and congestion internalization strategies (Kickhöfer and Kern 2014, Agarwal and Kickhöfer 2015, Kaddoura et al. 2014). While some of these studies investigated changes in the demand for competing modes in the presence of externalities, in contrast to the present work, they did not involve detailed public transit simulation. By modeling public transit modes that interact with passenger cars on the physical network representation, we more accurately simulate complex congestion dynamics resulting from mode shift decisions.
Policy mechanisms involving directly charging an agent with the social costs that he or she was responsible for have been evaluated by Kickhöfer and Nagel (2013) and Kaddoura et al. (2014). While effective in theory, and demonstrable in simulation, public support for congestion or emissions pricing remains lukewarm (Hårsman and Quigley 2010). Equity may also be a concern, as users with lower incomes may feel the effects of a toll disproportionately to more affluent users (Walter and Suter 2003). Furthermore, it is difficult to allocate revenues from greenhouse gas emissions costs, as their social costs may extend well beyond the major metropolitan areas considered for policy changes (Verhoef 1994). Further complicating As an alternative more in line with the sentiment that global problems can benefit from local actions, the current work demonstrates how an agent can exploit his social connectivity and the slack in his daily schedule in order to secure access to the travel modality that maximizes both his personal as well as societal benefits.

3. Methodology
In this section, we present our formal model of strategic peer pressure behavior, which we have adapted from the original formulation by Mani et al. (2013) to take place within the larger context of an activity-based model of urban travel. As has already been well-established in the transportation modeling literature, the demand for travel is derived from an agent’s need or desire to participate in activities (e.g., shopping or working) (Bowman 1998, Hägerstrand 1970). Scheduling a daily activity-travel plan requires individual agents to make several hierarchically-structured decisions that satisfy spatiotemporal constraints, financial restrictions, professional obligations, and meet a variety of other considerations.

Herein, however, we narrow the scope of this complex decision-making process to focus on the impact that active interpersonal influence has on an agent’s travel mode choice in the presence of system-wide externalities arising from the concurrent execution of all agent’s plans on the physical network. In the present scenario, agents are made aware of externalities such as traffic and CO\textsubscript{2} emissions via penalties to the utility of their realized plans. In response, agents producing the fewest externalities (e.g., public transit users) may choose to exert pressure on their peers (e.g., agents who drive alone) in the hope that they will follow suit. It is expected that daily travel mode choices will vary for individual agents as they induce and respond to peer pressure. However, if localized changes coalesce into cascading network effects and, consequently, a sufficient reduction in externalities is achieved, we expect that, at system equilibrium, individual shifts towards socially cooperative modes will be sustained in the form of significant increases in socially cooperative mobility lifestyles.

The rest of this part of this section is organized as follows. In subsection 3.1, we define the baseline model as a single agent decision problem; albeit one solved simultaneously by many agents connected via a social network. We then describe how, in the presence of multiple agents—each attempting to
make optimal decisions—we transform the baseline model into a two stage multiple player game. In subsection 3.2 we incorporate the effect of peer pressure and describe its effect on agent behavioral preferences. To aid in comprehension, subsection 3.3 presents a toy numeric example. Finally, in subsection 3.4 we describe the details of a full-scale implementation of our modeling framework in the multi-agent travel microsimulation.

3.1. Baseline Model

Agent decision-making behavior may be modeled as a repeated game played sequentially on consecutive days, \( t = (1, 2, \ldots) \), by a set of agents \( N = \{1, \ldots, n\} \). Agents are interconnected via a social network \( G = (N, E) \), where \( E \subseteq N \times N \). Each agent, \( i \in N \), has at most \( K \) peers in their neighborhood, \( \text{Nbr}(i) = \{ j : (i, j) \in E \} \), such that the graph representing the social network is sparse. An ordered pair of vertices \( (i, j) \in E \) denotes a directed social tie emanating from \( i \) and incident upon another agent \( j \); conversely, the pair \( (j, i) \in E \) denotes a directed edge from \( j \) to \( i \). In our formalism, the meaning of edges starting and terminating at the same vertex is undefined, so \( E = \{(i, j) \in 2^N \mid (i \neq j)\} \). The social network structure is assumed to be static: links between agents are fixed and link formation and destruction processes are undefined. For simplicity, ties are assumed to be reciprocal in strength.

At the beginning of each day \( t \) an agent \( i \in N \) chooses a single activity-travel plan \( x_{it}^m \) from a finite individual set of accumulated plans \( \mathcal{X}_{it} \), where \( \mathcal{X}_t = \{ \mathcal{X}_{1t} \times \ldots \times \mathcal{X}_{nt} \} \) is a set of combinations of potential plans available on the given day. The selected plan \( x_{it}^m \) represents a mental model of \( i \)'s schedule on day \( t \), which execute in a physical model of the network environment. More specifically, the physical model simulates the spatiotemporal dynamics of daily interactions between agents’ vehicles on a capacity-constrained transportation network that permits travel between the activity facilities at times specified by the schedule. The full history of an agent’s executed plans is denoted \( \mathcal{H}_i \).

A vector of plans, which we term an action profile \( \mathbf{x}_t \), represents the outcome of the plan selection process for all \( N \) agents. The action profile indicates which plans to simultaneously execute in the physical layer. Once a plan has been executed, an agent may choose to modify the plan based on beliefs of future system performance, which themselves are updated conditional on information gathered from their past experiences. Due to the competition of agents for finite road access, subway car space, and other transportation infrastructure capacity constraints, the quality of an agent’s plan depends on the decisions \( \mathbf{x}_{t-1} \) of the \( N \setminus \{i\} \) other agents, which we denote \( -i \). However, the behavior of \( i \) is primarily conditioned on the behavior of agents in \( i \)'s social network, \( j \in Nbr(i) \), and so perfectly Bayesian inference drawn from past information cannot be assumed. This specification is in accordance with empirically-validated game theoretic models of social learning that assume agents
possess imperfect information about the decisions of most agents in the network, which results in less than fully rational choices (Choi et al. 2009). Furthermore, in order to better capture constraints on human abilities to remember and adapt to the specifics of their daily travel experiences in a dynamic, multi-agent urban environment, agents occasionally forget plans that they rarely execute.

An agent $i$’s memory $X_i$, is a fixed size vector, containing tuples of previously experienced plans, $x_{it}^m \in \mathcal{H}_i$ and a corresponding utility score $U_{it}^m$. A removal rule is associated with each $X_i$, which ensures that agents maintain bounds on the cardinality of $X_i$, i.e., $|X_i| = M$ at any time $t$.

The solution concept for the physical system is, in this case, an agent-based stochastic user equilibrium (SUE) (Flötteröd and Kickhöfer 2016). Let $x^*$ denote the steady-state action profile that is consistently selected and executed at equilibrium. Once SUE is achieved, for all $t$, each agent is assumed to select plans, $x_{it}^m$ from a fixed memory, $X_i^*$, that maximize his enjoyment of activities while minimizing other marginal private costs (MPC) associated with scheduling choice dimensions such as travel mode, route, activity destination, departure time, etc. These attributes are represented as a vector, $a_{it}^m$. Once $x_{it}^m$ is selected and executed, the total utility that $i$ derives from the plan over the course of day $t$ is partially governed by a systematic utility function, $V_{it}^m = V(a_{it}^m) \forall m$. The systematic utility of a single plan for agent $i$ is a linearly-weighted combination of attributes for the plan:

$$V_{it}^m = \beta_{it}^m \top a_{it}^m,$$

where $\beta_{it}^m$ is a vector that parametrizes the marginal utility of plan $x_{it}^m$’s attributes. At SUE, agents are generally fully conscious of the attributes governing their own choice of optimal plan, although they may only be vaguely aware of the attributes governing other agents’ choice of plan.

Assuming that the random terms $\varepsilon_{it}^m$ are independently, identically distributed type I extreme value, the plan selection probabilities in the baseline model are assumed to be specified by a multinomial logit discrete choice model,

$$P(x_{it}^m \mid X_{it}) = \frac{e^{\mu_i V_{it}^m}}{\sum_{k \in X_{it}} e^{\mu_i V_{it}^k}},$$

where $\mu_i$ is a heterogeneous scale factor measuring the agent’s preference for higher scoring plans serving as a rationality parameter, where $\mu \to \infty$ corresponds to a deterministic choice of the best performing plan. This assumption corresponds to the standard random utility model (Train 2003, Ortúzar and Willumsen 2011).

When planning his day, an agent typically ignores the marginal external costs (MEC) that execution of their preferred plan in the physical environment imposes on other agents. In order to
account for agent preferences in the presence of aggregate external costs, we introduce an externality function, \( \nu_{it} : x_{-i,t} \to \mathbb{R} \) representing the disutility experienced by \( i \) due to \( x_{-i,t} \). The total utility of plan selection for agent \( i \) on day \( t \) is then defined as:

\[
U_{it}^m(x_{it}, x_{-i,t}) := V_{it}^m - \nu_{it} \left( \sum_{j \neq i} x_{jt} \right). \tag{3}
\]

In order to lighten notation, we drop further indexing on \( t \) and \( m \). The sequential nature of simulation and memory effects are highlighted wherever it is germane.

In the physical model, agents travel between activities by either driving a car or by using some more socially cooperative form of transportation (e.g., public transit or walking). At equilibrium, every agent is assumed to have a preferred choice of transportation mode corresponding to the plan \( x_i^m \in X_i^* \) with maximum \( U_i^m \). We denote \( \text{mode}_i(X_i^*) \in \{\text{car}, \text{sc}\} \) as the preferred transportation mode for a single agent at SUE. A driving agent is an agent for whom \( \text{mode}_i(X_i^*) = \text{car} \), and, likewise, an agent that prefers to commute using socially cooperative modes of transportation has \( \text{mode}_i(X_i^*) = \text{sc} \). While agents may have forgotten the details of previously selected plans when considering a change in the choice of transportation mode used during daily travel, they do remember the utility associated with their best past experience of the different modes used during plan execution.

An agent is also assumed to be generally aware of the primary transportation mode that his neighbors \( j \in Nbr(i) \) prefer to use. Let \( \kappa_i = \{ j \in Nbr(i) \mid \text{mode}_j(x_i^*) = \text{car} \} \) denote the subset of agents in \( i \)'s social network who prefer commuting using a personal vehicle, and, likewise, \( \psi_i = \{ j \in Nbr(i) \mid \text{mode}_j(x_i^*) = \text{sc} \} \) denotes agents who prefer socially-cooperative alternatives to driving alone. Define \( \Delta U_i = \Delta U_i(X_i) \) as the utility gap, which expresses the difference between the utility score of \( i \)'s equilibrium plan and the utility of the best scoring socially cooperative (i.e., transit or walking) plan in \( i \)'s memory, which we denote

\[
x_{i,sc}^o := \arg \max_{(x_i) \in \{x_i \mid x_i \in X_i^* ; \text{mode}(x_i) = \text{sc}\}} U_i(x_i, x_{-i}).
\]

The social surplus is defined as the sum of utilities experienced by all agents following plan execution:

\[
S(x) := \sum_{i \in N} U_i(x_i, x_{-i}). \tag{4}
\]

The action profile optimizing social surplus is denoted \( x^o \). In the presence of externalities, we know that the social welfare at the equilibrium action profile, \( x^* \) is suboptimal, since marginal social costs (defined as the sum of MECs and MPCs) no longer reflect an agent’s willingness to pay (Verhoef 1994). Therefore, at equilibrium \( S(x^*) < S(x^o) \).

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3 This specification is made in accordance with empirical research in behavioral economics on peak-end bias (Fredrickson and Kahneman 1993, Carrel et al. 2013).
3.2. Modeling Peer Pressure

By allowing agents to engage in peer pressure, the social costs implicit in the production of externalities can be internalized, bringing the social welfare of our model of the transportation system economy closer to the optimal value. We introduce peer pressure into our model as follows.

Let the matrix \( P \in \mathbb{R}^{n \times n}_+ \) denote the peer pressure profile, consisting of elements \( P_{ij} \) indicating the pressure that \( i \) exerts on peer \( j \). If \( j \not\in Nbr(i) \), then \( P_{ij} = 0 \). For agent \( i \), \( p_{↑i} \) (corresponding to the \( i \)th column of \( P^\top \)) is a vector of peer-pressures \( P_{ji} \). Likewise, \( p_{↓i} \) is the \( i \)th column of \( P \) consists of the vector of peer-pressures \( P_{ij} \).

The utility function with peer pressure is

\[
U_i(x_i, x_{-i}, P) = V_i(x_i) - \nu_i \left( \sum_{j \neq i} x_j \right) - \sum_{j \in Nbr(i)} P_{ji} - c \sum_{j \in Nbr(i)} P_{ij}, \tag{5}
\]

where the third term is the cost applied if \( i \) is pressured, while the fourth term is applied to the utility function as a sum of the costs accrued for \( i \) pressuring other eligible peers in his immediate social network. The marginal cost of peer pressure for each agent is \( c \) utils per unit of pressure. This parameter is indicative of the ease or difficulty with which one agent may pressure another agent. While in this study \( c \) is specified to be constant and homogeneous across the population, an agent-specific marginal cost of peer pressure can be considered in future work.

An agent-specific pressure selection strategy initially specifies which agents may pressure each other. We specify two such strategies below, followed by a detailed presentation of the peer pressure profile selection algorithms in Section 3.4.3.

For the first strategy, we specify that an agent who uses public transit or some other socially cooperative mode can pressure any peer in her neighborhood who drives. For any agent \( i \) whose equilibrium mode choice, \( \text{mode}_i(X_i^*) = \text{car} \), peers \( j \in \psi_i \) are permitted to pressure \( i \) to consider using an alternative to driving. Thus, in this strategy, peer pressure on \( i \) can only be activated if

\[
\sum_j P_{ji} \geq \Delta U_i = U_i(x_i^*, x_{-i}) - U_i(x_i^0, x_{-i}). \tag{6}
\]

Implicit in this criterion is a measure of accessibility to driving alternatives. Thus, people who do not retain a memory of public transit use at SUE would automatically be excluded from being pressured, as it would be too costly for any peer or group of peers to pressure them.

As a further strategy, we specify that an agent \( i \) who drives and has a utility gap greater than agent \( j \in \kappa_i \)'s utility gap,

\[
\Delta U_i > \Delta U_j,
\]

can pressure \( j \). This predicate measures the extent to which captive drivers would pressure other drivers with access to alternative commute modes to shift off driving in order to potentially benefit from reduced congestion.
Figure 1  Example social network of three agents i, j and k. Agents i and k currently commute via public transit and wish to pressure j, who currently drives to work, to also take public transit.

3.3. Example

<table>
<thead>
<tr>
<th></th>
<th>i</th>
<th>j</th>
<th>k</th>
</tr>
</thead>
<tbody>
<tr>
<td>mode(X₀)</td>
<td>sc</td>
<td>car</td>
<td>sc</td>
</tr>
<tr>
<td>V(x₀)</td>
<td>100</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>ΔUᵢ</td>
<td>0</td>
<td>20</td>
<td>0</td>
</tr>
<tr>
<td>νᵢ,ₐ(x₀, x₋₀)</td>
<td>-14 ~ 0</td>
<td>-14</td>
<td></td>
</tr>
<tr>
<td>U₀(x, x₋₀)</td>
<td>86</td>
<td>100</td>
<td>86</td>
</tr>
</tbody>
</table>

Table 1  Elements of utility computation without peer pressure. Social welfare is 272 utils.

<table>
<thead>
<tr>
<th></th>
<th>i</th>
<th>j</th>
<th>k</th>
</tr>
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<tbody>
<tr>
<td>pⱼ</td>
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<td>20</td>
</tr>
<tr>
<td>U(x₁, x₋₁)</td>
<td>84</td>
<td>100</td>
<td>84</td>
</tr>
<tr>
<td>mode(X₁)</td>
<td>sc</td>
<td>sc</td>
<td>sc</td>
</tr>
<tr>
<td>U₁(x₁, x₋₁)</td>
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<td>100</td>
</tr>
<tr>
<td>ΔS(x₁)</td>
<td>12</td>
<td>-20</td>
<td>12</td>
</tr>
</tbody>
</table>

Table 2  Elements of utility computation with peer pressure for c = 0.1. Social welfare at equilibrium is 280 utils.

We now examine a simplified numeric example that walks the reader through the computations performed during a round of the peer pressure game set in a fictitious travel environment. For simplicity, we will assume that units of utility are represented as utils. Consider a ‘society’ of three roommates (Figure 1), represented by agent ids i, j, and k, who commute to the same job (i.e., they all have the same home and work facility locations). We assume that each person derives an identical total utility of 100 utils from their daily activity schedule. Agents i and k typically commute via a municipal metro rail line. These two agents suffer from the greenhouse gas contributions of a mutual friend, agent j, who prefers driving an SUV to work over taking the train by ΔUⱼ(x₀) = 20 utils. Agent j’s action results in a 14 utils disutility due to CO₂ emissions, which is felt by i and k equally. As public transit riders, i and k do not produce externality through their respective actions. The parameters associated with Equation 3 are quantified in Table 1. The net social welfare in this situation is S(x) = 100 + 86 + 86 = 272 utils.
Now, suppose that agents $i$ and $k$ both pressure $j$, (recall that $p_{ij} = \Delta U_j$ in Equation 5) to leave his SUV in his garage and join them on the train. Assuming that the marginal cost of pressure, $c$ is 0.1 utils/unit pressure, the cost of pressure $j$ for $i$ and $k$ is $p_{ij} = p_{jk} = c\Delta U_j = 2$ utils. Agent $j$ then avoids the inconvenience of the $-40$ utils of peer pressure that he would otherwise suffer by indicating that he will join $i$ and $k$ in the near future. Table 2 illustrates that the initial cost of pressure lowers overall social welfare by four utils to 268 utils during the iteration that pressure is applied. However, if $j$ is true to his word, then each pressuring agent stands to gain 12 utils over the base case without pressure, amounting to an overall improvement in social welfare to 280 utils.

In this situation, the strategy of pressuring $j$ at iteration $q$ benefits both $i$ and $k$ by 12 utils in a future iteration. In this initial implementation, agents $i$ and $k$ don’t necessarily “learn” the benefits of pressure through the utility scores; however, since the cost of pressure is less than their $\Delta U_i$ scores for any $q$, engaging in peer pressure does not cause them to prefer driving over public transit. This indicates that as long as $i$ and $k$ continue to use public transit, peer pressure of $j$ is a stable equilibrium strategy.

### 3.4. Implementation overview

In order to implement the peer pressure game in a setting that allows for its economic evaluation in large, disaggregated urban transportation environments, we extend an existing open source activity-based travel microsimulation platform, MATSim (Horni et al. 2016). This subsection briefly outlines the simulation runtime cycle, the operation of the congestion and emission externality modules, as well as the implementation of the peer pressure extension developed for this work. Scenario evaluation with peer pressure differs significantly from the state-of-the-art use of MATSim-based tools and is described below in detail.

#### 3.4.1. Simulation platform. The core MATSim system is an open source development effort that facilitates demand modeling, dynamic traffic assignment, mobility simulation, and analysis. Several extension modules provide additional functionality applicable to modeling a variety of policy analysis scenarios. The extant MATSim API, employed extensions, and software developed as part of the current study are written in Java with associated analysis scripts developed in Python.

Every scenario simulation execution proceeds in an iterative manner according to the following four steps:

1. **Preparation.** During a single iteration, a simulated population of agents execute plans representing the typical daily home-based work tours. Plan elements consist of activities alternating with travel legs that describe the routes taken between activities. The activities have attributes of type (*e.g.*, home, work, leisure, etc.), location, start time, and duration, while the trip legs have attributes of mode, departure time, distance, as well as elements describing the traversal of routes...
through the network (e.g., links used, type of links, and total distance traveled). If a population’s initial plans are not available with fully detailed routes, one of the several available shortest path algorithms is used to calculate initial idealized daily trajectories.

2. Mobility Simulation. Following initial route assignment, the daily plans of the agent population are executed in the physical layer, which is represented by the links and nodes comprising the virtual road network topology. Public transit supply for modes such as subway or train are modeled on links and nodes that route vehicles separately from the road network [Rieser and Nagel 2010], while buses share the links with general traffic unless a dedicated transit lane is available.

3. Scoring. Agents have a configurable memory that permits them to choose between previously executed plans. In order for agents to simulate decision-making that models human behavior, an econometric utility function assigns a numeric score to executed plans plans [Charypar and Nagel 2005]. Specifically, for agent $i$ a plan, $x_i^m$, once executed, is assigned a score $V_i^m$, according to the time spent performing activities and the time spent traveling to and from activities,

$$V_i^m = \sum_{i=1}^{N} (V_{\text{perf},i} + V_{\tau,i} + V_{\text{late},i}).$$ \hspace{1cm} (7)

The utility earned due to time spent engaging in activities, $V_{\text{act},i}$, is a function of the time spent performing the activity $\tau_{\text{act},i}$:

$$V_{\text{act},i}(\tau_{\text{act},i}) = \beta_{\text{act}} \cdot \tau_{\text{typ},i} \ln \left( \frac{\tau_{\text{act},i}}{\tau_{0,i}} \right),$$ \hspace{1cm} (8)

where $\beta_{\text{act}}$ denotes the marginal utility of performing an activity for its typical duration, $\tau_{\text{typ}}$. At equilibrium, $\beta_{\text{act}}$ is the same for all activities and is equivalent in magnitude to the penalty applied to being late to an activity. The parameter $\tau_{0,i}$ scales the actual time spent performing the activity $\tau_{\text{act},i}$ by the activity’s priority and minimum duration, and may be ignored as long as dropping activities is not permitted.

Traveling is associated with a utility penalty, which varies according to trip cost $c_i$ and the mode-specific perception of trip travel time. The drive-alone mode-related parameters are subscripted with car and the alternative public transit mode is subscripted with pt. While walk-to-transit and walking modes are included in the simulation, they are not detailed here to simplify the notation. Travel-related utility scores are computed according to the following expressions,

$$V_{\text{car},i} = \beta_{\tau,\text{car}} \cdot \tau_{i,\text{car}} + \beta_{c} \cdot c_{i,\text{car}}$$ \hspace{1cm} (9)

$$V_{\text{pt},i} = \beta_{0,\text{pt}} + \beta_{\tau,\text{pt}} \cdot \tau_{i,\text{pt}},$$ \hspace{1cm} (10)

which are linear in the alternative-specific cost and time parameters: $\beta_c$ and $\beta_\tau$, respectively. In accordance with random utility theory, the $\beta_0$ terms are alternative-specific constants (ASCs) that
characterize other factors that systematically predispose individuals to choose one alternative over another (Train 2003, Ben-Akiva and Lerman 1985).

In order to represent a typical 24-hour period, the first and last activity are considered in the same iteration such that there are the same number of trips and activities.

4. **Replanning.** Following scoring, the most recently executed plan is stored with a configurable number $M$ of previously executed plans, $X_i$, in system memory. At the beginning of the subsequent iteration, agents choose a new plan based on a configurable selection module and an optional route modification module. In this study, innovative modification strategies include: changing the departure time, link sequence (route), and choice of transit-related modes including legs performed by walking. While the default configuration specifies that agents select their current best score for modification, we opt to use a probabilistic sampling strategy to achieve a more realistic distribution of agent plans for selection, as given by Equation 2. The plan with the worst score is then dropped from the agent’s memory, and the modified plans are simulated again.

Steps 2-4 are repeated until a stochastic user equilibrium is reached.

3.4.2. **Computing and Applying Externalities.** Once a baseline calibrated scenario has been derived, the travel behavior of the study population is permitted to evolve in the presence of externalities. That is, the simulation steps described in subsection 3.4.1 are repeated except that agents are made aware of the effects of congestion and emissions due to the decision of other agents to drive. Herein, as described in subsection 3.1, we assume external costs are globally distributed, and are consequently applied as in Equation 3.

The following paragraphs briefly review design choices used in this study to simulate agent air emission and congestion externalities. The adopted methodology is derived from (Agarwal and Kickhöfer 2015) that studies the shift from private to public transit due to emissions and congestion pricing.

**Emissions.** Costs associated with air pollution due to emission of combustion gases during driving activities are computed following the work of (Kickhöfer and Nagel 2013). Emissions calculations are performed on a link-by-link basis, tying attributes of a traveler’s vehicle and road conditions to air pollution parameters. Since road type and quality affect pollutant levels, initial routing computations are modified to anticipate this additional cost, such that agents may choose to travel on roads that avoid creating excess emissions.

Herein, as opposed to earlier work using this module, we consider CO$_2$ production only. This study investigates the effects of externalities that result in a more diffuse social cost, and, therefore, are more difficult to internalize through regulation. Other automobile exhaust constituents do, indeed, result in transportation externalities, however we restrict the computations to arguably the most representative one for simplicity. Accordingly, we focus on the global warming potential (GWP) of CO$_2$, and do not simulate the damages due to other emissions.
Congestion. Road network congestion is computed as in \cite{Kaddoura2014} by taking advantage of the queue model that underlies the traffic flow simulation. In free flow conditions, agents take $\tau_{\text{free}}$ to traverse a link. A maximum of $c_{\text{flow}}$ agents may leave a link in a given time span. Any link traversal by an agent prevents following agents from accessing the next link until $\frac{1}{c_{\text{flow}}}$ has passed, resulting in delays, $d_{\text{flow}}$. Spill-back delays ($d_{\text{storage}}$) may also arise if the storage capacity $c_{\text{storage}}$ of a link, measured in number of vehicles, is exceeded.

Delays are measured in seconds and computed as the difference between the free speed travel time ($\tau_{\text{free}}$) and the travel time experienced by an agent ($\tau_{\text{exp}}$):

$$d_{\text{tot}} = \tau_{\text{free}} - \tau_{\text{act}} = d_{\text{storage}} + d_{\text{flow}}$$

(11)

During the replanning stage, agents take into account delays due to congestion accrued in the previous iteration, potentially motivating less congested routes or mode shift.

3.4.3. Simulating Peer Pressure. The eligibility of agents to participate in the peer pressure distribution stage is described in the methodology section \ref{section:methodology}. The algorithm is outlined in Algorithm \ref{algorithm:peer-pressure} with the conditions defining an agent’s eligibility to pressure and be pressured provided, for clarity, as flowcharts in Figure \ref{figure:peer-pressure-flowcharts}. In order to simulate the effect of peer pressure, we modify the mode change strategy to potentially reroute the just completed plan for public transit. Once members of a driving agent’s social network sufficiently pressure him to consider an alternative mode, their most recently executed plan is then flagged. Flags expire after a number of iterations equal to the size of the agent’s memory. Thus, if, through the plans sampling process, an agent does not choose the flagged plan by the expiration iteration, the plan will no longer be eligible for rerouting until the agent is pressured again. The expiration condition models the idea that the memory of social influence is ephemeral, people do not always behave as they and that not every attempt of pressure will be successful.
Algorithm 1 Peer Pressure Algorithm

for $i \in G$ do
    if isEligibleForPressuring($i$) then
        $p_{\uparrow i} \leftarrow 0$
        for $j \in \text{Nbr}(i)$ do
            if isEligibleToPressure($j$) then
                $p_{\uparrow i} \leftarrow p_{\uparrow i} + \Delta U_i$
            end if
        end for
        if $p_{\uparrow i} > \Delta U_i(x)$ then
            $U_i \leftarrow U_i - \Delta U_i$
            flag($x^*_i$)
        end if
        for $j \in \text{Nbr}(i)$ do
            if isEligibleToPressure($j$) then
                $U^m_j \leftarrow U^m_j - c\Delta U_i$
            end if
        end for
    end if
end for

4. Case Study

In order to verify the functionality of the peer pressure algorithm on a large scale travel demand scenario, we have applied the framework described in section 3 to a simulation of San Francisco Bay Area daily commute traffic.

4.1. Simulation Data Sources

4.1.1. Network. The road network, consisting of 96,000 links, and representing freeways, state routes, all major arterials, and countryside roads, was generated from Open Street Map data.

We use a fully integrated public transit routing module (Rieser and Nagel 2010), permitting a highly detailed simulation of Bay Area public transit throughout the course of the day. Physical track and scheduling data for the public transit system are derived from General Transit Feed Service (GTFS) data and include 9 major transit agencies operating light rail, metro and bus routes. The initial modal split has been calibrated to passenger counts obtained from the regional transportation
planning authorities, the Metropolitan Transportation Commission. See Figure 4 for a map of the transit lines used in this study.

4.1.2. Initial Plans. The population of the study area in 2015 was approximately 7.5 million people. Of the estimated 3.4 million commuters, 75% drive alone, while 11.5% take public transit and 3.5% walk to work. A base population of synthetic commuters, comprising 50% of the Bay Area was adopted from the Bay Area Travel Model One of the Metropolitan Transportation Commission, and adjusted with anonymized cell phone data logs. Cell phone data records (CDRs) are collected and managed by a major national carrier were recorded at the spatial resolution of cell phone towers. Home and work locations generated from these CDRs are upscaled to match the marginals of the population census, and then sampled to produce a desired number of agents in the synthetic population. A complete methodology of generating activity-based travel demand models from cellular data is described in (Yin et al. 2017).

Due to the computational requirements of composing the emission, congestion, and the detailed simulation of public transit, as well as the social network and peer pressure simulation developed as part of this project, a 1% sample of the full synthetic population was used. The spatial distribution of the synthetic agents home locations split by the commute mode of the initial plan set is illustrated in Figure 3. It is instructive to compare modal split to the layout of the transit network in Figure 4.
Table 3 Behavioral parameters of the utility functions specification.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Value</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta_{\text{perf}}$</td>
<td>Marginal utility of performing activity</td>
<td>1.205</td>
<td>util · hr$^{-1}$</td>
</tr>
<tr>
<td>$\beta_{\text{late}}$</td>
<td>Utility of late arrival</td>
<td>-18</td>
<td>util · hr$^{-1}$</td>
</tr>
<tr>
<td>$\beta_{\tau, \text{car}}$</td>
<td>Marginal utility of time (car)</td>
<td>-0.134</td>
<td>util · hr$^{-1}$</td>
</tr>
<tr>
<td>$\beta_{\tau, \text{pt}}$</td>
<td>Marginal utility of time (public transit)</td>
<td>-0.16</td>
<td>util · hr$^{-1}$</td>
</tr>
<tr>
<td>$\beta_{\tau, \text{walk}}$</td>
<td>Marginal utility of time (walking)</td>
<td>-0.29</td>
<td>util · hr$^{-1}$</td>
</tr>
<tr>
<td>$\beta_{\text{wait}, \text{pt}}$</td>
<td>Marginal utility of waiting for public transit</td>
<td>-0.044</td>
<td>util · hr$^{-1}$</td>
</tr>
<tr>
<td>$\beta_{ls}$</td>
<td>Marginal utility of line switch</td>
<td>-0.045</td>
<td>util · hr$^{-1}$</td>
</tr>
<tr>
<td>$\beta_{0, \text{pt}}$</td>
<td>Alternative specific constant (public transit)</td>
<td>3</td>
<td>util</td>
</tr>
<tr>
<td>$\beta_{0, \text{walk}}$</td>
<td>Alternative specific constant (walking)</td>
<td>-1</td>
<td>util</td>
</tr>
<tr>
<td>$\beta_c$</td>
<td>Marginal utility of money</td>
<td>0.083</td>
<td>util · $^{-1}$</td>
</tr>
<tr>
<td>$\text{VTTS}_{\text{car}}$</td>
<td>Value of travel time savings for drivers</td>
<td>14.52</td>
<td>$\cdot$ hr$^{-1}$</td>
</tr>
</tbody>
</table>

Recognizing the limitations of using a small sample, in practice one has to face heavy computational loads of simulating detailed behaviors of 50,000 interconnected agents. As a result, network flow capacities for network links are scaled down to 1%. Following recommendations found in (Kickhöfer and Agarwal 2015), flow capacities are scaled to 3% in order to achieve realistic congestion patterns. Rescaling did not substantially affect the attainment of validation metrics.

4.1.3. Social Network Generation. No individual level personally identifiable information was used in the study. A synthetic social network for the population of 50,000 agents was generated. An algorithm used to generate ties in the network respects core statistics of the network graph (node degree distribution, clustering coefficient), as well as the household composition, the marginals of the socio-demographic attributes (age, gender, income) of nodes, and the macro-level spatial patterns of the network community structure. It involves using probabilistic Bayesian networks (Sun and Erath 2015) to match the conditional distributions of the socio-economic parameters describing the households composition, and the exponential random graph models (ERGM) (Schweinberger and Handcock 2015) to fit the identified network statistics and community structure parameters. The complete methodology of simulating a required social network was adopted from the algorithms of (Zhang et al. 2017).

4.1.4. Behavioral Parameters. Behavioral parameters used in the simulation and provided in Table 3 generally match the accepted specifications described in (Horni et al. 2016), Chapter 3, except for the values specific to the region in question. Particularly, the alternative specific constants for public transit were adapted to match the observed volumetric passenger counts. Additionally, the marginal utility of money, $\beta_c$ was derived from survey data used for the San Francisco Mobility, Access, and Pricing Study (SFCTA 2010).
4.1.5. Emissions Module Parameters. The existing emission extension developed in (Kickhöfer and Agarwal 2015) adheres to European standards, practices, and driving conditions. In order to better align with the local physical and regulatory transportation environment, the module’s source code was altered to be compliant with USEPA and (when available) California Air Resource Board (CARB) emission models. Emission factors used in simulation calculations are derived from the CARB’s EMFAC2014-LDA passenger vehicle model aggregates for the San Francisco Bay Area Air Quality Basin (California Air Resources Board 2014). Emission monetary costs are computed using the United States Environmental Protection Agency’s Social Cost of CO$_2$ statistics (IAWG 2015). These are provided at variable discount rates (1, 3, and 5%). We use the moderate $36$/tonne CO$_2$ derived using the 3% discount rate as a reasonably conservative measure of the social cost of carbon, noting that a value of as high as $120$/tonne may be used in particularly risk averse scenarios. As in (Kickhöfer and Nagel 2013), we assume that public transit use has negligible emissions in comparison to automobile travel.

4.2. Simulation Experiments

The workflow for the simulation experiments performed in this study are presented in Figure 5. Individual steps are discussed below.
4.2.1. **Baseline scenario.** A base case is first established for policy comparison purposes. To derive a baseline scenario, agents are permitted to adaptively optimize their routes, modes, and departure times for 100 iterations in the presence of system-wide externalities, as described in [subsection 3.4.2](#). Prior to each iteration 20% of agents selected at random will have either their selected plan rerouted, trip departure/arrival times modified, or the travel mode for their daily commute will be shifted from private to public transportation. We calibrate the congestion and emission externalities using linear scaling factors of $10^{-5}$ and $10^{-4}$ respectively so that they contribute in the order of 10% of the typical agent score. While quantifying the influence of globally-distributed negative externalities as well as environmental awareness on individual decision making
is largely an open research problem, in the present we follow [Agarwal and Kickhöfer, 2015] to set this order of magnitude.

The output plan data from the final iteration of the base model with externalities are used in welfare comparisons.

4.2.2. Peer pressure scenario. In the peer pressure experiments, utility is assigned according to Equation 5. For each run of the policy case, the value of $c$ (marginal cost of pressure) is set beforehand and innovative strategies are maintained as before.

Peer pressure is specified to begin after 5 iterations to verify that the start point of the run is equivalent to the base case end point. Innovative strategies are retained in order to permit agents to modify and optimize their plans in response to peer pressure. We run the simulation with pressure and innovative strategies until iteration 80, at which point plan innovation is turned off. This was done to view how the system relaxes when plans are fixed.

The algorithm used to implement peer pressure in the microsimulation context is provided in Figure 2. Recall from Equation 5 that the parameter, $c$, is the marginal cost of pressure. For all agents in a simulation run, we assume a homogeneous value of $c$. In the present study, all peers, $j \in Nbr(i)$ will pressure $i$ as long as they are eligible to do so. For example, under the first pressure
strategy, if there are $|\psi_i| > 0$ peers eligible to pressure an agent $i$, then $U_i$ will be penalized by $\Delta U_i$ utils and each $j \in \psi_i$ will be penalized $c\Delta U_i$ utils. Then, the change in social welfare for the system due to peer pressure under profile $x$ is given by $\Delta S_p(x) = -\sum_{i \in N}(1 + c|\psi_i|)\Delta U_i$ utils.

Since empirical data on the social cost of peer pressure in this context is unavailable, we performed a sensitivity analysis by running the simulation for a range of magnitudes of $c$, ranging from 0.001 to 10, while holding all other parameters constant.

5. Results
5.1. Peer Pressure: Effect on Mode Shift and System Dynamics

In this section, we examine the effect of peer pressure on mode shift and score evolution as well as how system dynamics and target metrics vary with the marginal cost of peer pressure, $c$.

![Figure 6](image1.png)

**Figure 6** Net number of agents shifted to socially cooperative modes for different values of the marginal utility of peer pressure.

(a) Average scores of agents when $c < 1$.  
(b) Average scores of agents when $c \geq 1$.  

![Figure 7](image2.png)

**Figure 7** Ensemble average score sensitivity of agents to value of $c$. Scores are in utils.
In Figure 6, the number of agents that switch mode between iterations is plotted over time at different values of $c$. While it is evident that the amount of agents shifted is inversely proportional to the value of $c$, some aspects of the evolution of shifts in travel mode are independent of the value of $c$. Clearly, for all of the values of $c$ explored, *ceteris paribus*, peer pressure is effective in achieving attenuation in the net number of drivers. Once innovative strategies are turned off, at $t = 80$, the number of shifted agents eventually drops to 0, as expected, since, at this point, agents only select between existing plans in their plansets. Although the simulation with peer pressure was not run to convergence, we observe in Figure 6 that the maximum number of agents shifted per iteration does appear to be reaching a fixed point.

When exploring the dynamics of the system as a function of $c$ and $50 < t \leq 80$; however, we observe that a phase transition in the stability of system evolution may occur between $c = 0.01$ and $c = 1$. Specifically, in Figure 6, we note that for $c = 0.001$ and for $c = 0.01$ at $t > 50$, the number of agents shifted begins to oscillate around an upward trending baseline. These oscillations are on the order of $1 \times 10^3$ agents and have a period of 10 iterations. This second order phenomenon is almost entirely absent in the simulation for values of $c \geq 1$.

For $c = 0.01$, Figure 8 demonstrates that the number of agents pressured and mode share are roughly covariant. This observation suggests that oscillations in the system evolution occur due to synchronization of pressure-induced mode shift forcing and ephemeral memory effects in a segment of the pressured population. That is, while peer pressure-induced mode shift generally improves utility for many agents (as demonstrated by the overall increased uptake in travel mode), some
Table 4  Externality internalization due to peer pressure

<table>
<thead>
<tr>
<th></th>
<th>Congestion Delays (hrs)</th>
<th>CO₂ Emissions (tonnes)</th>
<th>($)</th>
<th>($)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Before Pressure</td>
<td>53,275</td>
<td>770,360</td>
<td>3,085</td>
<td>111,072</td>
</tr>
<tr>
<td>After Pressure</td>
<td>15,946</td>
<td>230,584</td>
<td>2,205</td>
<td>79,373</td>
</tr>
<tr>
<td>Net Change</td>
<td>-37,329</td>
<td>+539,776</td>
<td>-881</td>
<td>+31,699</td>
</tr>
</tbody>
</table>

Note: Values taken at iterations 0 and 80. Value of travel time savings of car mode, VTTS_{car}, taken as 14.52 $ · hr^{-1}. Social cost of carbon assumed to be $36.00/tonne under a 3% discount rate.

pressured agents would have been better off driving. Isolating the optimal population that would benefit from pressure will be treated in future work.

The ensemble average score evolution plots (Figure 7) present the values of the executed, worst, average, and best plans in an agent’s plan set, \( X_i \), averaged over all agents as a function of the iteration, \( t \). We have separated the plots of ensemble average scores into two subfigures in order to better illustrate how the dynamics of the system evolution vary with \( c \). For values of \( c < 1 \), mode shift apparently covaries with score evolution, as suggested by the oscillations in scores depicted in Figure 7a. For \( c \geq 1 \); however, Figure 7b indicates a catastrophic collapse in the executed and worst agent scores, with particularly unstable scores observed for \( c = 10 \).

The precipitous decrease in executed plan scores at high values of \( c \) clearly leads to unsustainable dynamics wherein the disutility imposed by peer pressure exceeds the utility of plan execution. We therefore present the rest of our results and analysis for simulation outputs where \( c = 0.01 \), which we take as a moderate value consistent with the more realistic utility scores observed for lower values of \( c \).

5.2. Quantifying Changes in Externalities

Table 4 demonstrates that pressure leads to a reduction in travel delays of 37,329 hours. When multiplied by the VTTS of travel by car, this is equivalent to a net social gain of $539,776. The $31,699 gain from CO₂ abatement is a slightly less significant improvement. As suggested by the results presented in subsection 5.1 congestion improvements are due to agents switching from driving alone to transit-oriented modes in response to the active influence of peers in their social group.

As shown in Figure 9 the distribution of changes in link travel time indicates that not all travelers experienced improvements even though changes in delays on links were reasonably evenly distributed. A spatial analysis of the redistribution of monetized delays is indicative of the winners and losers of peer pressure as well as where changes in travel time occur. Figure 10 shows the delay cost differences between the business as usual (\( t = 0 \)) and peer pressure (\( t = 80 \)) case experienced by agents visualized as an average over all agents with home locations in a traffic analysis zone.
Figure 9  Link delay difference distribution between base case (iteration 0) and peer pressure case (iteration 80) \( c = 0.01 \).

(TAZ). Evidently, the greatest improvements in congestion due to peer pressure are experienced by people living in less populated areas. It is instructive to compare total delays experienced by agents on their individual trip routes to delays of all agents on a link-by-link basis\(^4\) (Figure 11). The greatest improvements happen on freeways and arterial routes, which is somewhat expected, since the greatest proportion of agents travel over these links. In some rural areas, congestion does appear to increase. Long distance commuters from the rural areas are taking more direct routes to the urban core due to the congestion relief therein, but end up queueing on the approaches. The agents traveling along these routes are unable to pressure their peers to stop driving in order to reduce congestion due to unavailability of alternative modes. This observation suggests that these users may benefit from increased access to public transit, or park and ride facilities.

We observe differences in the distributions of pressured (Figure 12) and pressuring agents (Figure 13). Initially, pressured agents are, as expected, clustered around public transit. However, over the course of the simulation, as feedback between pressured and pressuring agents grows, we see that pressurees become more evenly dispersed throughout the Bay Area. Pressuring are generally distant from sources of public transportation and remain so throughout the simulation. Qualitatively, locations where agents are closer to transit seem to correspond to some of the most improved travel times (Figure 11). In Figure 12 we can see that, over the course of the simulation, the distribution of pressured agents becomes relatively more concentrated in these areas.

\(^4\) These delays are measured according to the difference between free-flow travel time and estimated travel time averaged over the 24 hour simulation period
6. Conclusions

This work describes an agent-based simulation framework developed to model the effects of peer pressure on inducing socially-cooperative travel mode choice. By applying the aggregate effects of externalities on agents explicitly and providing a mechanism for agents to, effectively, negotiate time valuation, an efficient redistribution of social welfare is achieved.

Due to the stochastic interaction of agents during the mobility simulation, it is not possible to develop a closed-form optimal pressure strategy for agents to pursue. Thus, many heuristic strategies and solution search algorithms may be explored in order to develop system-optimal pressure behavior. For example, the decision for an agent to apply pressure may be contingent on how many other neighbors the agent can pressure (as well as their pressure costs), whether other neighbors will participate, and, considering that pressure can be applied to the same person in repeated iterations, how successful past attempts were.

Despite demonstrating that peer pressure leads to widespread improvements in congestion and reductions in emissions, the spatial analysis of post-pressure changes shows that some areas are worse off. This finding highlights the need to ensure that policy proposals be sensitive to social justice issues, particularly if travel time and emission improvements are unequally biased towards
Figure 11  Road links with improvements (shown in green) and delays (shown in red) based on differences between experienced and free speed travel time between iterations $t = 0$ (business as usual) and $t = 80$ (peer pressure).

one demographic or another. Running the simulation with demographic data and heterogeneous preferences accordingly may improve the representativeness of results as well as help communities understand the potential impacts of cyber-social influence.

When reduced externality costs are insufficient to encourage modality shifts away from driving, policy instruments can be used to incentivize agents to pressure their peers. However, the role of governments in achieving cooperative outcomes in social dilemmas need not be a coercive (Ostrom 1990, Ostrom et al. 1992). In light of the analysis on incentivizing peer pressure described in (Mani et al. 2013), extensions to our framework can be used to design public transportation policy that subsidizes the social costs of peer pressure with the goal of improving net social welfare. For example, a municipality can encourage positive peer pressure by providing a bonus to drivers who encourage their friends to carpool to work with them.

While designing rewards to subsidize peer pressure is a topic left for future research, the work presented herein is not without its practical merits. Simulating the positive effects of peer pressure on social welfare may motivate citizens to make decisions that equitably address commons problems by demonstrating how social networks spread and stabilize behavior change arising from local interactions. That is, by propagating simulated information from the virtual world to the real world,
Figure 12  Evolution of pressured agent spatial distribution through several iterations.

people can learn under what circumstances the personal cost that they incur in pressuring their peers would result in net personal and social benefits. Alternatively, our framework can be used to inform individuals if peer pressure is not worth the loss in social capital due to excessive free-riding; encouraging policy makers to fund the gap. Providing unbiased and clear information will ensure that policy nudges promote democracy rather than co-opt autonomy.

References


Figure 13  Evolution of pressing agent spatial distribution through several iterations.

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