## WORKING PAPER

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# Snowball effect and traffic equilibrium in a market entry game: A laboratory experiment.

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**TITLE:** **Snowball effect and traffic equilibrium in a market entry game: A laboratory experiment.**

**ABSTRACT:** The Market Entry Game (Selten & Guth, 1982; Gary-Bobo, 1990) is a coordination game where average cost of entry increase linearly. Following the suggestion of Anderson et al. (2008) and empirical evidence in transport economics suggested by related literature about the Speed-Flow Relationship (Verhoef, 2005), we built a theoretical model of market entry game where congestion cost increases at an increasing rate when the flow of entrants grows (snowball MEG). The calibration of experimental parameters enables us to compare outcomes regarding Snowball MEG to a benchmark based on a usual linear MEG (calibration being the same as in Anderson et al., 2008). Then, we run an experiment where theoretical predictions for both models give comparable entry rate and add more or less the same properties. Moreover, we conduct variation about group size in order to assess size effect on coordination level. Basically, we find no significant difference between the aggregated entry rates in our snowball game compared to usual MEG. But size clearly matters, especially for issue regarding successful coordination for users in the snowball MEG.

**KEY WORDS:** ***Coordination game; loss aversion; experimental economics; road congestion; speed-flow relationship.***

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# 1 Introduction

Talking very generally, congestion refers to a situation where the cost (payoff) function for a given agent is restricted to be solely a function of the number of people that might use a given resource.

More precisely, congestion games (Rosenthal, 1973) are non-cooperative games in which a player's strategy is to choose a subset of resources, and the utility of each player only depends on the number of players choosing the same or some overlapping strategy. For such congestion games, it is generally shown that Nash equilibria lead to inefficient outcome (See Correa et al., 2008). The lack of efficiency could be measured by the Price of Anarchy (Papadimitriou, 2001), which denotes the ratio of the worst social cost of a Nash equilibrium to the cost of an optimal solution.

Congestion cost might be represented in many ways, the easiest being a separable and affine cost function where the cost is to be increased linearly when the utilization rate grows.

In recent years, there had been a increasing number of experimental studies devoted to traffic congestion games situations. All these studies relate to particular congestion games based upon different theoretical models of congestion. For instance, Ziegelmeyer et al., 2008 or Daniel et al., 2009 made lab experiments based on a discrete version of a bottleneck model (Vickrey, 1969 ; Arnott, De Palma & Lindsey, 1993). Differently, Morgan et al., 2009, Rapoport et al., 2009, Hartman, 2009 and Denant-Boemont & Hammiche (2012) try to observe within the lab some paradoxes that could be produced by Wardrop-Nash equilibrium when users have to choose among routes (Braess Paradox) or among modes (Pigou-Knight-Downs Paradox, Downs-Thomson Paradox). The common feature of all these experimental games is that congestion cost is assumed to be a linear function of the entrants number on a given route, mode, etc. Such assumption implies in particular that the marginal congestion cost of user is the same whatever the number of users having already entered on a route is.

Such an assumption may be viewed as very specific since considering real-world traffic congestion, one might expect that congestion cost increases not linearly, e.g. exponentially with traffic level. Indeed, a very well-known stylized fact in transport economics is that speed (cost) decreases (increases) very rapidly when the number of users on a given route begins to rise. This stylized fact, formerly established in the 1930s years by traffic engineers, is known as the "speed (cost)-flow relationship" (Greenshields, 1935 ; Walters, 1961 ; Verhoef, 2005). In the recent years, this fundamental relationship had been questioned (See Kerner, 1999 ; 2004) but remains empirically a acceptable assumption at the macroscopic level (see Taylor et al., 2008).

This paper investigates how variations in technology cost function might affect users' coordination in a very specific congestion game, the Market-Entry Game (MEG). Such a coordination game, introduced by Selten & Guth, 1983, applies for various situations, not only to traffic congestion, but also for competition between firms for instance (Goeree & Holt, 2005). The MEG is a very simple game and represents an elegant stylization of congestion problem: In the MEG situation, $n$ players are simultaneously confronted to simple binary decisions, whether to enter a market or not, entry payoff being a decreasing function of the total number of entrants, and exit decision associated with a fixed payoff. MEG is a coordination game with many (asymmetric) pure or mixed - symmetric or not - strategy Nash equilibria, but all these equilibria have the property to be inefficient.

If agents are purely rational and selfish, MEG situation will produce therefore a social dilemma (as defined by Kollock, 1998). Many experimental works, beginning with Kahneman, 1988, studied this particular class of coordination games (Erev and Rapoport, 1998 ; Rapoport et al., 1998, 2000, 2002 ; Ochs, 1998 ; Camerer & Lovallo, 1999 ; Seale and Rapoport, 2000 ; Duffy & Hopkins, 2005).

In particular, the experimental study by Anderson et al. (2008) uses a Market Entry Game to simulate a traffic coordination problem, and aims at observing how congestion charges (entry pricing) or real-time information given to participants as fictitious users might improve efficiency. In the conclusion, Anderson et al. (2008) notice: *"The linear congestion function used in this experiment is, for some purposes, a little too forgiving in the sense that small increases in traffic often have "snowball effects" that increase congestion dramatically".* Such a intuition is precisely what is suggested by a huge empirical evidence related to speed-flow relationship, used for for instance by Vickrey (1963) to represent travel time cost functions for road users.

Nevertheless, even if the empirical evidence in transport economics clearly suggests a non-linear form for congestion cost, to our knowledge, no experimental study had ever been done in order to observe how coordination process among users that will finally raise traffic equilibrium might be affected by such a characteristic. Our idea is therefore to assess the impact of non-linear congestion on the way users coordinate individual decisions and to which traffic equilibrium they will converge. More precisely, the key question being about the impact of a quadratic cost function - implying that average travel time increases at an increasing rate as traffic flow rise -, what will be the behavior of experimental users compared to others that are to be confronted to the usual linear cost function? We conjecture that, possibly suffering for very high transport costs as traffic level increases, road users might hesitate much more about entering on a given road compared to a situation where additional cost for a marginal user is constant. To test our conjecture, we build a laboratory experiment where participants play different specifications of Market Entry Games, some having to decide entering in a road where congestion cost increases rapidly (snowball Market Entry Game), and others being placed in the usual linear Market Entry Game. Theoretical predictions for both specifications result in the same Pure Strategy Nash equilibrium entry rate, that enables us to compare clearly observed equilibrium among specifications regarding congestion technology. Our results are the following. Even if congestion cost grows rapidly in our snowball market entry game, the average entry rate is not significantly different from the usual linear MEG, even if the number of participants to our traffic games is to be increased. Moreover, entry rates that are observed are very similar to Pure or Mixed Strategy Nash equilibrium predictions. Of course, as observed behavior is close to equilibrium predictions, aggregated outcomes are inefficient, and participants as road users do not succeed to solve the congestion externality problem.

Our paper is organized as follows. The first section is devoted to a literature review about the speed-flow relationship, which gives us empirical support for our theoretical model for snowball MEG. The second section presents theoretical models (linear MEG and snowball MEG) and the experimental design. The third section is related to experimental results and the last section is to conclude.

## 2 Congestion Cost and Speed-Flow Relationship

Relationship between speed and traffic flow, defined generally as the number of vehicles per unit of time, is generally viewed as being non linear (Sorensen et al., 2008). Implication of this is that the effects of adding few more vehicles onto the road depend on the number of vehicles already using the car. Indeed, the effect of an additional vehicle on a given road is more and more damaging for average vehicle speed. Nevertheless, the initial calibration by Greenshields (1935) describes a linear relationship between speed and flow (see the left side of figure 1). But since that, there is much more empirical evidence indicating that time-average speed-flow relationships as being non linear, and potentially described by a power law that was initially used by Vickrey (1963). Such hyperbolic functions are chosen in order to take into account the fact that the impact of increasing traffic density is very minor for low traffic volumes and gets more and more obvious when traffic density increases. Of course, with such functions, marginal cost of congestion could be very high if traffic flow becomes important compared to linear congestion function, as it is pointed by Doll & Jansson (2005).

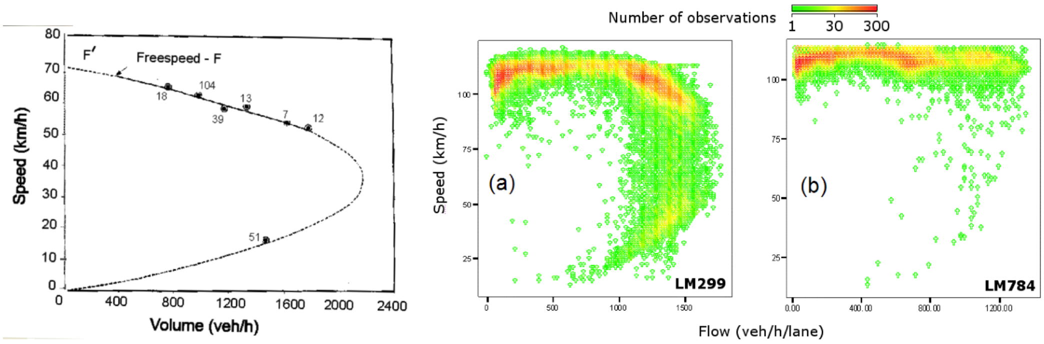


Figure 1: (Empirical) Speed-Flow Relationships (source: Taylor et al, 2008)

Walters (1961) observed that the inverse of speed (travel time per unit road length) multiplied by the constant length $X$ of the road and by the value of time (assumed to be exogenous and constant) reflects the average (time) costs AC per trip (ignoring other costs of travel). Consequently, the backward-bending speed-flow function thus implies a backward-bending AC-curve, which is depicted in Figure 2.

Two areas can be distinguished in the following figure. The first one, named "normal congestion", corresponds to a situation where average cost increases first very slowly as traffic flow rises and then begin to increase very rapidly when capacity is to be reached. In this area, average cost increases with traffic flow. When traffic flow equals road capacity, average cost continues to rise but traffic flow begins to decrease, i.e. a negatively sloped backward bending part, which corresponds to what is called "hypercongestion" (Small & Chu, 2003). In this latter part, average cost could grow to infinite value whereas traffic flow can be very reduced, and, at limit, as traffic could be totally stopped, flow equals zero and AC grows to infinite.

As speed is inversely related to (average) private transport time (or cost) for users, Small (1992) shows that is possible to approximate the relationship between average time travel during a given period and average flow over that period (time-averaged relationship) by

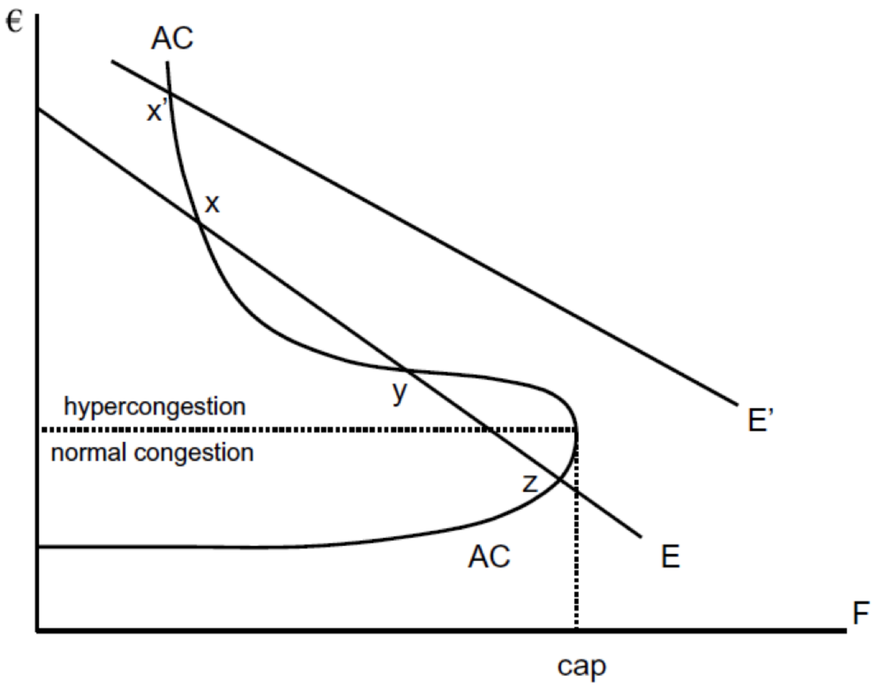


Figure 2. The backward-bending average cost curve (AC) and two inverse demand curves (E and E0) defined over traffic flow (F) (source: Verhoef, 2005)

using, as suggested by Vickrey (1963), the power law function (See also Small & Chu, 2003). The relationship resembles typically to the following:

$$AT = T_0 + T_1 \left(\frac{\lambda}{q_b}\right)^{\xi} \tag{1}$$

with $\xi >>> 1$, where $\lambda$ is vehicle flow, $q_b$ the capacity of the way.
In the transport economics literature, the estimated value of $\xi$ depends necessarily on the kind of road infrastructure, lying between 2.5 from 5 (Small & Verhoef, 2007). For instance, for a freeway, this value lies around 4 whereas for arterials, it is nearly 2.5. In our experimental design, we will assume that this parameter equals 2, since our goal is simply to implement a snowball effect in a public facility that is congestible.

# 3 Theoretical model and experimental design

## *3.1 Characterization of Market Entry Games*

### 3.1.1 Traffic Equilibriums in the case of a Linear Market Entry Game

The Market Entry Game is a very elegant stylization of a congestion process. In this game, introduced by Selten and Güth, 1982 and Gary-Bobo, 1990, a given number of $n$ players have to choose simultaneously and independently whether or not to enter a market. In the most simple formulation (See Erev and Rapoport, 1998), payoffs are linear with the number of entrants. For instance, if player $i$ strategy is $\delta^i = 0$ stay out, or $\delta^i = 1$ enter, then her payoff is

$$\pi_i(\delta) = \begin{cases} k, & \text{if } \delta^i = 0 \\ k + r(c - m), & \text{if } \delta^i = 1 \end{cases} \tag{2}$$

$k$, $r$ and $c$ are positive constants and $0 \leq m \leq n$ being the number of entrants. The constant $c$ can be interpreted as the capacity of the market. In such a model, the return of entry exceeds the return of staying out iif $m \leq c$.

There are many (asymmetric) pure strategy Nash equilibria for this class of games. If $c$ is an integer, any profile of pure strategies which is consistent with either $c$ or $c-1$ entrants is a Nash equilibrium. If $c$ is not an integer, a pure strategy Nash equilibrium involves exactly $c$ entrants where $c$ is the largest integer smaller than $c$. Moreover, if $c$ is not an integer the number of Nash equilibria is finite, while if $c$ is an integer there is a continuum of equilibria[1].

The latter have the following form: $c-1$ players enter, $N-c$ stay out, and one player enters with any probability. Furthermore, this implies that only when $c$ is not an integer are the pure equilibria strict.

Additionally, for $c > 1$, there is a Symmetric Mixed-Strategy Nash Equilibrium (MSNE) where $p^* = \frac{c-1}{n-1}$ (See Rapoport, 1995 ; Sundali et al., 1995), $p$ being the probability for player $i$ to enter, under the assumption that players are risk neutral. The symmetric mixed strategy Nash equilibrium (for risk-neutral players) is given by equating the expected payoff of entry for a player $i$ and the certain payoff of staying out, that is:

$$\underset{s=0}{\overset{s=n-1}{}} C_{n-1}^{s} p^{s} (1-p)^{n-s-1} \{k + r(c - s - 1)\} = k \tag{3}$$

Where $s$ is the number others players to enter. The expected number of entrants assuming that each player follows MSNE, is then defined by:

$$t(c) = np^* = \frac{n(c-1)}{n-1} \tag{4}$$

As the probability to enter can be viewed as the parameter of the binomial law, the standard deviation of the expected number of entrants $np^*$ is $\sqrt{\left(\frac{c-1}{n-1}\right)\left(1 - \left(\frac{c-1}{n-1}\right)\right)n}$. (See Rapoport, 1995 ; Erev & Rapoport, 1998).

Moreover, as it is reported by Duffy & Hopkins (2005), there is also in such a one-shot game Asymmetric Mixed Strategy Equilibriums[2].

[1] An interesting discussion about the theoretical properties of several coordination games, in particular the Market-Entry game, but also other games, can be found in Anderson & Engers, 2005.

[2] These additional asymmetric mixed equilibria imply that $j < c-1$ players enter with probability one, $k < N-c$ players stay out with probability one, and the remaining $N-j-k$ players enter with probability $(c-1-j)/(N-j-k-1)$ . In one of these asymmetric mixed Nash equilibria, the expected number of entrants is $j + (c-1-j)(N-j-k)/(N-j-k-1)$ which again is between $c$ and $c-1$ . Note though that as $k$ approaches $N-$c, the expected number of entrants approaches $c$.

To sum up, the important common feature of all these Nash equilibria is that the expected number of entrants is between $c$ and $c-1$. On the welfare level, such a game implies a social dilemma since all possible equilibria are inefficient (Erev & Rapoport, 1998), i.e. efficiency is not maximized when $n=c$ or $n=c-1$ if $c$ is sufficiently high[3]. If we compute social welfare, defined as the sum of payoffs for the entire group and assuming that $c$ is to be an integer, we have

$$W = m\left(k + r\left(c - m\right)\right) + \left(n - m\right)k \tag{5}$$

Social welfare is maximized when $m^{**} = \left\{\frac{1}{2}c\right\}$. Then, Nash equilibrium will be consistent with maximizing efficiency if and only if $c$ is sufficiently small (here $c \leq 2$). Moreover, in this characterization, $m^{**}$ does not depend upon the total number of users.
As it is noted by Duffy & Hopkins (2005), the (linear) MEG does not belong to pure coordination games, where agents have an incentive to take alltogether the same action. In this case, the successful coordination involves that agents take different actions, where some should enter and the others staying out. The consequence is that, given that symmetric outcome should be particularly salient (all players enter or all players stay out), repeating the one-shot game will help individuals to learn to condition their behavior on the behavior of others and hence converge to an asymmetric equilibrium.

### 3.1.2 Traffic equilibriums in the case of a Market Entry Game with Snowball effect

Using eqn (1) which defines Average Travel time (cost) per user, and if it is assumed that each user get a fix reward $F$ per journey, we can define Average Payoff $AP$ as

$$AP = \left(F - T_0\right) - T_1\left(\frac{\lambda}{q_b}\right)^{\xi}$$

If users are homogenous, and if entry decision is simultaneous, average payoffs are symmetric for users, i.e. $AP$ corresponds to user's individual payoff. Assuming that parameter $\xi$ equals 2 (congestion function is quadratic), we can define payoff function for MEG with Snowball effect as:

$$\pi_i\left(\delta\right) = \begin{cases} v, & \text{if } \delta^i = 0 \\ k - r\left(\frac{m}{c}\right)^2, & \text{if } \delta^i = 1 \end{cases} \tag{6}$$

With the same notations that in linear MEG, with $v > 0$ and assuming that $c$ is an integer, any profile of pure strategies which is consistent with either $c$ or $c-1$ entrants is a Nash equilibrium, as in the linear MEG. Moreover, there is a symmetric mixed-strategy Nash equilibrium where the probability to enter is $p^* = \frac{c\left(\sqrt{\frac{(k-v)}{r}}\right)-1}{n-1}$[4]. If we assume that $(k-v) = r$, the probability to enter is the same as in the linear MEG, i.e. $p^* = \frac{c-1}{n-1}$.

[3] But PSNE are Pareto-rankable since the total payoff for $m=c-1$ is higher than for $m=c$. The same remark applies for Snowball MEG.

[4] The probability to enter is obtained by equating the payoff of entry to the payoff of non-entry in the Snowball MEG, and by replacing m by the following equation that $m = p\left(n-1\right)+1$.

In the same vein, for Snowball MEG, the maximum level of Welfare - defined as the total payoff for the entire group - is

$$W = m\left(k - r\left(\frac{m}{c}\right)^2\right) + (n-m)\,v \tag{7}$$

Applying simply F.O.C. regarding $m$ variable derives the number of entrants that maximizes social welfare. The maximizing-welfare solution corresponds therefore to $m^{**} = c\left(\sqrt{\frac{(k-v)}{3r}}\right)$.
That is, snowball MEG and linear MEG have the same Nash equilibriums, but entry rate that maximizes efficiency is higher for snowball MEG i.i.f $k - v > \left(\frac{3}{4}\right) r$. Of course, the same remark as before applies here: Like Linear MEG, Snowball MEG implies asymmetry in actions to be taken by individuals, which means that repetition might help them to coordinate better.

## *3.2 Experimental design*

### 3.2.1 Calibration of One-Shot Congestion Games and Theoretical Predictions

Our aim is to compare coordination and efficiency levels in our two games, the linear MEG and the quadratic MEG. Our conjecture is that, by incurring a payoff that decreases very sharply as the entry rate grows in the snowball MEG, with potential very high losses in case of high entry rates, participants should hesitate more much to enter the market than in the linear MEG. Moreover, if Pure strategy Nash entry rate do not depend on group size, it is not the case for Mixed Strategy entry rate that depends on $n$. For this reason, we have two additional treatments that consist in doubling group size, all others parameters being kept constant.

In the linear MEG studied by Anderson et al. (2008), the payoff function corresponds to

$$\pi_i(\delta) = \begin{cases} 0.5, & \text{if } \delta^i = 0 \\ 0.5 + 0.5\,(8-m)\,, & \text{if } \delta^i = 1 \end{cases} \tag{8}$$

This payoff function will correspond to our benchmark treatments, corresponding to Linear Market-Entry Game.
In MEG with Snowball effect, we will have the following payoff function

$$\pi_i(\delta) = \begin{cases} 0.5, & \text{if } \delta^i = 0 \\ 4.5 - 4\left(\frac{m}{8}\right)^2, & \text{if } \delta^i = 1 \end{cases} \tag{9}$$

For the two games, for a common capacity $c = 8$, and for our *ad hoc* specific values of parameters $k, r$ and $v$, (Asymmetric) Pure Strategy Nash Equilibrium (PSNE) occur when entry rate $m$ equals 8 or 7. Symmetric Mixed-Strategy Nash Equilibrium (MSNE) corresponds to a probability to enter the market that is $p(e)^* = \frac{7}{11}$ in the case when $n = 12$ and $p(e)^* = \frac{7}{23}$ in the case when $n = 24$. If it is assumed that players adhere to

MSNE, then standard deviation of entry rate is respectivly $\sigma(e) = 1.67$ when $n = 12$ and $\sigma(e) = 2.25$ when $n = 24$.
In the case of Linear MEG, maximum efficiency is reached when $m^{**} = 2 = \frac{c}{2}$. For Snowball MEG, as it was indicated above, maximum efficiency is to be obtained for $4 < m^{**} < 5$.
Our experiment consists in a 2X2 design, depending on group size ($n = 12$ or $n = 24$) and on congestion technology (snowball MEG or linear MEG), implying as a consequence four possible experimental treatments. Each subject participate to a session that consists in a total number of 24 participants, with three distinct parts. For the first two parts, and in order to control for subjects heterogeneity, we choose to implement a within-subject design where each subject participate to two successive market entry games with two different group sizes, congestion technology remaining constant for a given participant. More precisely, two experimental conditions were implemented, the first one where group size is to be increased (INC condition) whereas in the second one it is to be decreased (DEC condition). In the INC condition, a given participant belongs in a first step to a group of 12 participants, including himself, and has to decide whether or not he enters a market with a specific payoff function depending on entry rate (from 1 entrant to 12 entrants). Such a decision is repeated 20 periods, such an information being given at the beginning of the experiment, groups being held constant (partners design). In the second step, group size rises from 12 to 24 and the same participant interacts with subjects that belong to the entire session, i.e. 23 other participants, and such during another 20 periods. In the DEC condition, we simply reverse the order for group size, that is a given participant interacts first in a group of 24 players during 20 periods and second in a group of 12 subjects during another 20 periods. Such a procedure enables to control for order effect. The last part is a real-payoff experiment that aims at eliciting loss aversion for each participant. Participants were aware that the experiment will have three parts and know that, the two first parts will consist in the same situation repeated during 20 periods. But they did not know at the beginning of the experiment what they will face as a situation during parts 2 & 3.
At the end each period, in parts 1 & 2, subjects get information about total number of entrants and their own individual payoff. This information reveals both payoffs, for entrants and non-entrants of course, and also enables them to calculate the entire group payoff[5]. Moreover, during all periods of parts 1 & 2, their computer screen displays a table that describes past history, i.e. if participants are to choose to enter or to stay out in period 3, they were aware about entry rate and their own individual payoff for periods 1 & 2

The linear MEG is our benchmark treatment, and for this benchmark, only the INC condition was implemented. Moreover, after parts related to congestion games (parts 1&2), participants loss aversion was elicited by using the procedure based on Fehr & Goette (2007) and used for instance in Gaechter et al. (2007). This procedure is the following. Each subject was to choose between participating to a given lottery with 50% chances of incurring a potential loss $L$ and 50% chances for a potential gain $G$ and abandoning. Six similar choices are to be made, all things being constant but the potential loss. Lottery choices can be made in any order that is chosen by a participant. The following table describes the six lottery choice situations.

[5] Informations available for each subject are similar to the "aggregate information" treatment implemented in Duffy & Hopkins, 2005 for a linear MEG.

Table 1. Loss aversion task (real payoffs, adapted from Gaechter et al., 2007)

| situation | gain or loss | accept | reject |
|---|---|---|---|
| 1 | if "blue", you looses 2 euros ; if "red" you gain 6 euros | | |
| 2 | if "blue", you looses 3 euros ; if "red" you gain 6 euros | | |
| 3 | if "blue", you looses 4 euros ; if "red" you gain 6 euros | | |
| 4 | if "blue", you looses 5 euros ; if "red" you gain 6 euros | | |
| 5 | if "blue", you looses 6 euros ; if "red" you gain 6 euros | | |
| 6 | if "blue", you looses 7 euros ; if "red" you gain 6 euros | | |

Loss aversion in the risky task is determined by using cumulative prospect theory, as in Gächter et al, 2007. A decision maker is indifferent between participating to the lottery or quitting if $w^{+}(0.5)\, v(G) = w^{-}(0.5)\, v(L)\, \lambda^{risky}$ . Here, $v(x)$ is the value of the outcome $x \in \{G, L\}$ , $w^{+}(0.5)$ and $w^{-}(0.5)$ are respectivly the weights associated to a 50% chances of gaining $G$ or loosing $L$, and $\lambda^{risky}$ denotes the coefficient of loss aversion in the task. If it is assumed that $w^{+}(0.5) = w^{-}(0.5)$, like in the parametrization of Prelec (1998) about weighting function for probabilities, and considering that, due to the small size of G and L, we assume that $v(x) = x$, then level of loss aversion is $\lambda^{risky} = \frac{G}{L}$.
Details are now to be given in the next subsection regarding the way experimental data were collected.

### 3.2.2 Experimental sessions

Our sessions were conducted from June to November 2010 in the LABEX, University of Rennes 1. We had 360 participants, all being students from various formations, with a majority of first year of Bachelor in economics or business administration. The average payoff was around 15 euros, for an average total duration of 1h30'. All sessions were computerized by using ZTREE software (Fischbacher, 2007) and instructions were not framed in order to fit for a specific transport situation choice. Participants were invited to sessions by using ORSEE software (Greiner, 2004).
The following table describes more precisely our combinations of treatments and conditions (see table 1).

Table 2. Experimental treatments and conditions

| Condition | treatments | subjects | groups | sessions |
|---|---|---|---|---|
| INC-SNOW | Snowball MEG $n = 12$ / $n = 24$ | 120 | 10 (5) | 5 |
| DEC-SNOW | Snowball MEG $n = 24$ / $n = 12$ | 120 | 5 (10) | 5 |
| INC-MEG | Linear MEG $n = 12$ / $n = 24$ | 120 | 10 (5) | 5 |
| | | 360 | | 15 |

Our experimental set-up enables us to conduct therefore within-subjects comparison (for instance by comparing sequence INC-SNOW to sequence INC-MEG) in order to assess the effect of congestion technology on coordination level, and also to analyze group size effect in a between-subjects comparison.
In each technology (Linear MEG or Snowball MEG), the payoff function is defined according equations given above. Participant individual payoff is represented in figure 3 below.

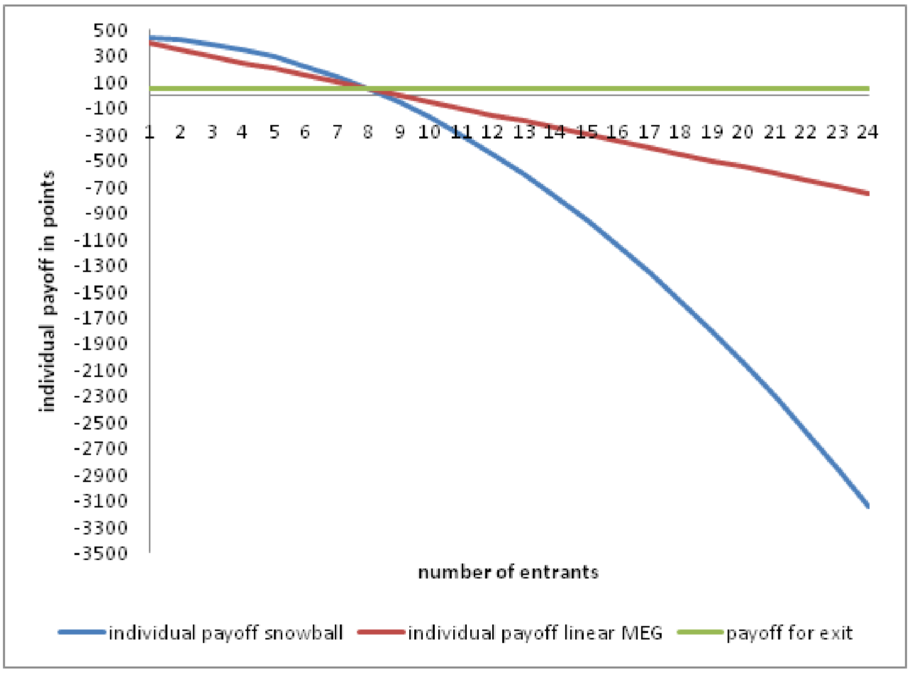


Figure 3. Individual payoff (in experimental points) for linear and snowball MEG

In particular, it has to be noticed that participants could experience losses, that could be very high for the treatment SNOW in the case of large groups. For instance, given the exchange rate that was given at the beginning of the experiment to participants (50 points for 1 euro), potential loss could be 63 Euros (namely 90 US dollars in June 2011) if group size was 24 and each participant enters. For limiting the impact of potential losses on decisions, we indicate to participants that 2 periods in the first part of the experiment and 2 other ones in the next part were to be randomly drawn as support for final payoff. The final payoff was a compound payoff of periods of part 1 and part 2, plus one among the six lottery choices made by each subject that is to be randomly chosen.

For the loss aversion task, the payoff was determined in the following way. First, a color corresponding to the issue of each outcome was randomly drawn (Blue for Gain, Red for Loss, with 50% chances for each). After that, one of the six decisions was randomly drawn for each subject. If the selected decision correspond to abandoning the lottery, the payoff was zero Euro. If she chooses to play the lottery, depending on color, Gain or Loss in Euros begins effective. At the end of the session, final payoff was the total payoffs over the 4 periods randomly drawn plus or less the payoff for the loss aversion task.

# 4 Experimental results

## *4.1 Aggregate Behavior: Entry rate*

### 4.1.1 Is there a Snowball effect on coordination levels?

One key question settled by our study is to determine whether or not agents tend to under entry with snowball treatment than with MEG treatment. The conjecture is the following: As participants might suffer from potential higher losses in the case of an increasing marginal congestion cost described through the snowball technology, individual risk or loss aversion should make entry decision to be considered very cautiously. Such a problem should be enhanced when group size is to grow. Table 2 indicates average entrants number and statistical dispersion around average entry rate for sessions that had been run under INC condition.[6]

Table 3. Average Entry rate (s.d.) per Treatment and Group Size

| Congestion Technology | snowball | linear |
|---|---|---|
| group size | | |
| $n = 12$ | 7.685 | 7.89 |
| | (1.71) | (1.71) |
| $n = 24$ | 8.91 | 8.61 |
| | (2.49) | (2.05) |

The first empirical evidence is that participants successfully coordinate around Pure Strategy Nash Equilibrium on average, which is in line with previous experimental works on Market Entry Game (see among others Rapoport,1995 ; Sundali et al., 1995 ; Erev et al., 1998 ; Erev et al., 2010), The correlation level between equilibrium predictions (MSNE) and observed entry rate is 0.75 for snowball MEG and 0.79 for linear MEG. Whatever experimental conditions, the average observed entry rate (defined as the ratio $\frac{m}{n}$) is very close to probabilities to enter predicted by MSNE, but tends to be higher when group size is large, indicating a propensity to over-enter when groups are to be large, or equivalently when relative capacity $c/n$ is low. Again, it is a common feature of experimental stylized facts about MEG, since subjects tend to over-enter when capacity is low and to under-enter when capacity is high (See Camerer and Lovallo, 1999).

In the INC condition, average entry rate $\frac{m}{n}$ is respectively 0.64 when $n = 12$ and 0.36 when $n = 24$ for snowball MEG, and respectively 0.66 and 0.38 for Linear MEG, to be compared to a common probability to enter being $p = 0.64$ when $n = 12$ and $p = 0.30$ when $n = 24$ at MSNE. But, from period to period, there is huge variations about entry rate, whatever technology is (see figure 4 below). Moreover, the level of coordination remains around trend that is consistent with Nash equilibriums and does not significantly improve with repetition, suggesting very few learning for participants.

Moreover, Kahneman (1988) states that the vast majority of trials in a linear MEG where capacity is exogenously changed at every period could be explained by a very simple equilibrium rule where $c - 2 \leq m \leq c + 2$[7].

Concerning our data, considering that capacity does not change, we have the following results (see table 4).

[6] As we do not run linear MEG in DEC condition (see table 1), we are not able to compare with our snowball sessions in DEC conditions. The only comparison to have is therefore for different technologies (linear vs snowball) that had been run for each under INC condition.

[7] As in Rapoport et al. (1995), we relax slightly the assumption of Kahneman by considering $|c - m| \leq 2$.

Table 4. Average frequency for the number of entrants close to capacity

| treatment | cumulative frequency of entrants number for $6 < m < 10$ |
|---|---|
| snowball, n=12 | 87.5 |
| snowball n=24 | 67.5 |
| linear MEG, n=12 | 87 |
| linear MEG, n=24 | 81 |

These results indicate that more than 80% of observed number of entrants lie between 6 and 10, which corresponds to the capacity more or less 2 units. The noticeable exception is the snowball MEG treatment with large groups, where this proportion is only around 2/3. Figure 4 below indicates the distribution of entrants number for each treatment.

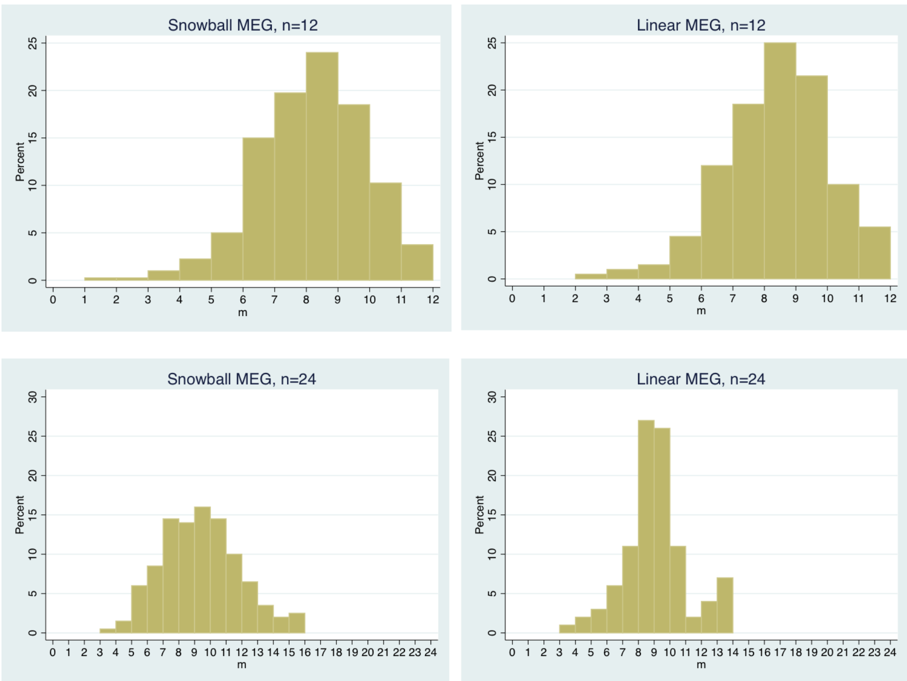


Figure 4. Distribution of Entrants Number per Treatment

This figure shows that the distribution of entrants number is rather similar for both technologies when group size is small, modal value being just at the capacity level ($m = c = 8$). But for larger groups, the spread of distribution for snowball MEG is larger than for linear MEG, suggesting higher dispersion for aggregate entry choice. Nevertheless, such an observation is not confirmed by a deeper statistical analysis, as it will be shown below.
The first surprising result is that, even if subjects could experience very high losses in the Snowball case, and given possible loss aversion for them, the average entry rate for Snowball technology is very near theoretical prediction given by PSNE assuming risk neutrality. Indeed, entry rates for both technologies are very close.
Our first result indicates consequently that the average entry rate do not significantly differ for snowball technology compared to linear one.

- *Result 1. Entry rate is not significantly different under Snowball MEG compared to Linear MEG treatment, whatever group size.*

Empirical evidence is here quite intriguing: When group size was equal to 12, average number of entrants was not significantly lower under Snowball technology than under linear MEG one (Wilcoxon Mann-Whitney rank-sum test, $z = 1.368$ ; $p = 0.1713$). The difference remained also not significant when group size was equal to 24 (Wilcoxon Mann-Whitney rank-sum test, $p = 0.8335$).
Last but not least, standard deviation was not significantly different under snowball MEG compared to linear MEG regardless the group size (for $n = 12$, a Wilcoxon Mann-Whitney rank-sum test indicates a critical probability being $p = 0.65$, whereas for $n = 24$, a similar statistical test indicates a critical probability $p = 0.4647$, which do not enable to reject the null hypothesis of equal standard deviation among our different MEG technologies).

Our second result relates to dispersion around Pure Strategy Nash equilibrium for each technology.

- *Result 2: Variation around average observed entry rate and PSNE is not different between snowball and MEG treatments, regardless group size*

Indeed, it is possible to conjecture that, under snowball technology, coordination around Nash equilibrium could be more difficult. The first reason for such a conjecture is that the variance of payoffs for snowball technology is much higher than in the linear case. The absolute range of payoffs is more than 3 times higher for snowball MEG and variance is 10 times higher when group size equals 24 (see figure 3). When group size is to be 12, the ratio of payoffs range is 1.625 when snowball is compared to linear MEG, and the variance ratio is around 2.8. In all cases, average payoff is higher for linear MEG. In fact, entry decision is very risky in Snowball MEG, and consequently, participants should be more reluctant to enter when exposed to this congestion technology. Moreover, since subjects could experience higher losses than in Linear MEG, potentially loss averse participants should try to find a stable outcome, avoiding too much deviations around it. Therefore, the possible consequence of that should be higher variance around average entry rate under Linear MEG compared to Snowball MEG. Such a conjecture is not totally supported by experimental data, as non parametrical statistics given previously show that standard deviations around average entry rate do not differ significantly between our two kinds of MEG, which is quite surprising. Figures 5 & 6 describe average entry rate respectively for INC condition and for DEC condition. In INC Condition, it is possible to compare aggregate behavior in Linear MEG compared to snowball MEG. In fact, even if non parametric statistics do not confirm such evidence, the dispersion around equilibrium seems to be less for Snowball treatments than for linear ones.
Such a result could be partially explained by heterogeneity in subject's loss aversion regarding our two different kind of sessions, i.e. snowball MEG vs Linear MEG. The basic results about loss aversion levels are reported in table 5 below.

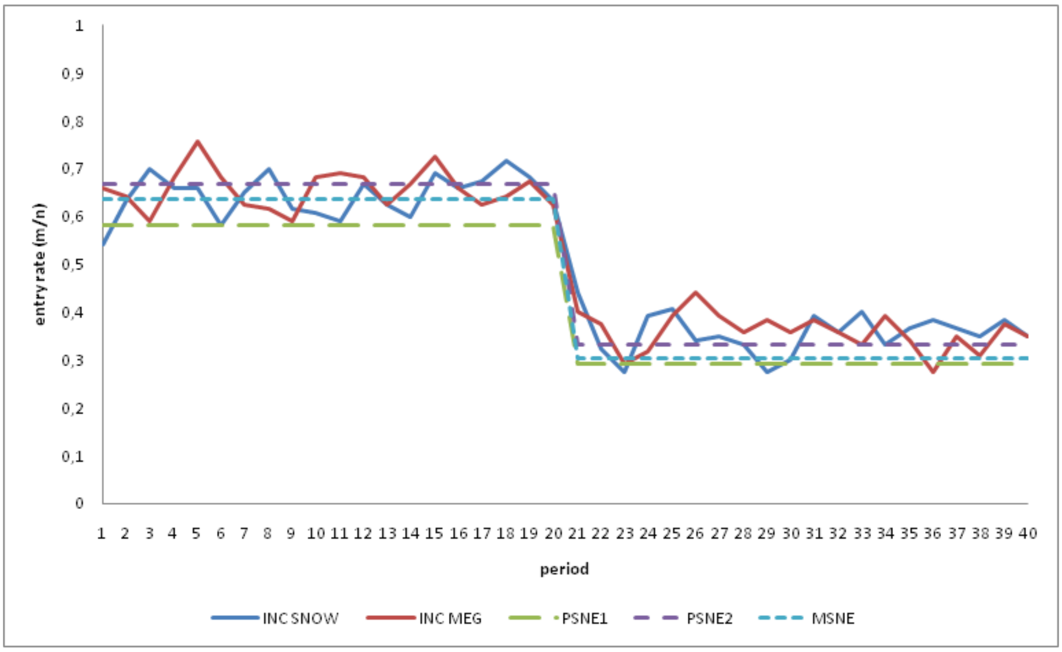


Figure 5. Entry Rate for each technology (Linear and Snowball MEG), "INCreasing" condition (NB: PSNE is Pure-Strategy Nash Equilibrium ; MSNE is Mixed-Strategy Nash Eq.)

Table 5. Summary statistics for participants loss aversion level $\lambda^{risky}$

| treatments | statistic | value |
|---|---|---|
| snowball MEG | average | 1.88 |
| | (s.d.) | (0.91) |
| | median | 2 |
| | Frequency of $\lambda > 1$ | 79% |
| linear MEG | average | 1.86 |
| | (s.d) | (1.01) |
| | median | 1.5 |
| | Frequency of $\lambda > 1$ | 71% |

Aggregate results about loss aversion levels are slightly above results obtained by Gaechter et al. (2007) for median values but very close for the frequency of having a $\lambda$ higher than 1, indicating strict loss aversion. They obtained a median value of 1.2 and a frequency around 70%. These results also indicate that loss aversion level is slightly higher for snowball treatments compared to linear treatments. But such an empirical evidence fails to be confirmed by parametric or non parametric statistics, difference between our two samples being non significant.

In DEC condition (see figure 6), average entry rate for snowball treatments lies around PSNE and MSNE, as in INC condition (see figure 5). But it is possible to notice that observed average entry rate is above Equilibrium entry rate when group size is to be low, indicating difficult coordination process for participants. Such empirical evidence is

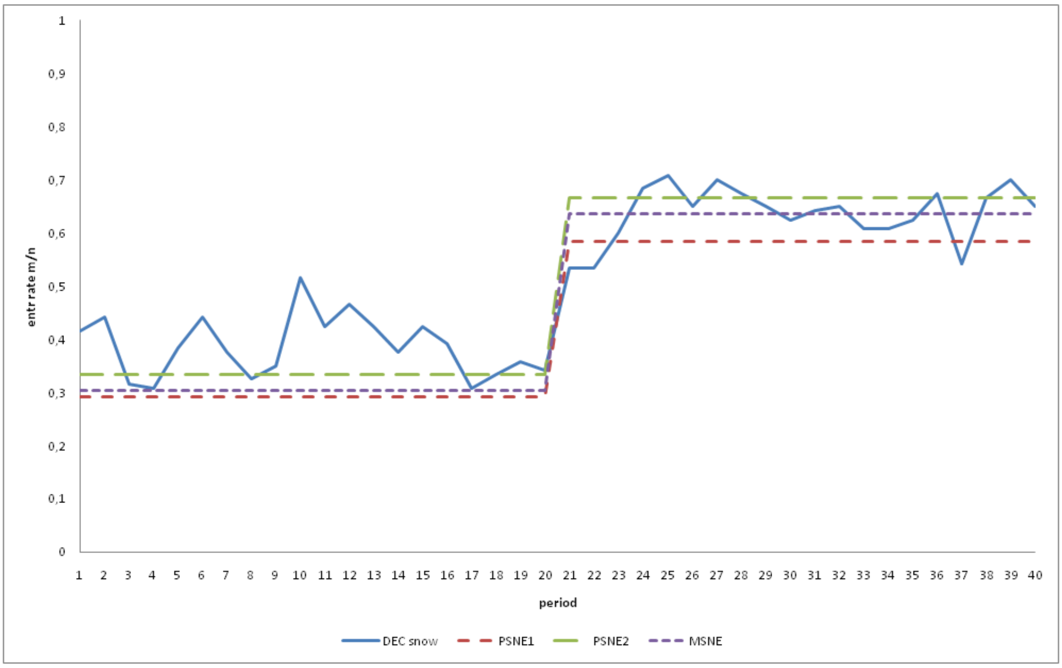


Figure 6. Entry Rate for each technology (Linear and Snowball MEG), "DECreasing" condition (NB: PSNE is Pure-Strategy Nash Equilibrium ; MSNE is Mixed-Strategy Nash Eq.)

underlined by a Mann-Whitney Rank Sum non-parametrical test about observed entry rate per group when $n = 24$ for DEC condition compared to theoretical MSNE entry rate ($z = -2.795$ ; $p = 0.0052$***), suggesting that observed entry rate is higher compared to the predicted one. The fact that there is no difference about entry rate between our two kind of MEG can be illustrated by parametric evidence. The table below reports the results of a Panel Probit analysis with Random Effects about the probability to enter, by controlling in particular individual loss aversion level, and group size and technology as dummies. More precisely, the estimated model is:

$$\Pr\left(\delta_i^t = 1\right) = \beta_1 \left(Order\right) + \beta_2 \left(Snow\right) + \beta_3 \left(size\right) + \beta_4 \lambda_i^{risky} + \beta_5 \delta_i^{t-1} + \beta_6 \pi_i^{t-1} + \beta_7 m^{t-1} + \beta_0$$

Results of this parametric analysis are given in the table 6 below.

Table 6. Estimates of a Panel Probit model with Random Effects about the probability to enter (pooled data)

| Explanatory variable | coeff (st. error) |
|---|---|
| Order (=1 if INC condition) | 0.041 |
| | (0.085) |
| Snow (=1 if Snowball MEG) | -0.075 |
| | (0.085) |
| Big Size (=1 if $n = 24$) | -0.711*** |
| | (0.029) |
| $\lambda_i^{risky}$ | -0.221*** |
| | (0.038) |
| $\delta_i^{t-1}$ | 0.889*** |
| | (0.031) |
| $\pi_i^{t-1}$ | -0.0007*** |
| | (0.000) |
| $m^{t-1}$ | -0.055*** |
| | (0.008) |
| constant | 0.797*** |
| | (0.147) |
| obs. | 12616 |
| number of subjects | 332 |

NB: ***: sign. at the 1% level ; **: at the 5% level ; *: at the 10% level

The results indicate that loss aversion tends to decrease propensity to enter, as past individual payoff and past entry level. The role of loss aversion is not in line with previous results obtained for instance in Erev et al. (2010), since in their experimental study, the proportion of choices of the risky alternative (to enter) does not appear to reflect risk aversion and/or loss aversion. Moreover, entering in the last period increases the probability to enter at the current period, and explanation for such a fact is difficult to find. As we noticed earlier in non parametrical evidence, the fact of being confronted to a snowball effect of congestion do not seem to play a different role on the probability to enter compared to linear MEG. But the propensity to enter is decreased when group size is large, since individuals could anticipate the difficulty of coordinating themselves on a reasonable issue, i.e. around entry levels above 6 and 10 for instance. This fact is not explained only by individual loss aversion, since regression controls for that variable.

### 4.1.2 Size effect

The impact of group size on coordination at the aggregate level is clear on a theoretical point of view. First, if it is assumed that participants adhere to PSNE or to MSNE, there should not be any difference about group size for the number of entrants since at the PSNE, the number of entrants equals capacity (or capacity minus one), and that, at MSNE, entrants number is the product of group size by the probability to enter. In all cases, the number of entrants $m$ should lies between $c - 1$ and $c$, without any difference regarding MEG technology (Linear or Snowball). The entry rate is of course impacted

by group size, whatever concept of equilibrium is used, since $n$ is a variable both of the probability to enter (MSNE) or a variable in the entry rate frequency.
An important result here is that, when group size is higher, even is capacity do not change from one treatment to the other, and all thing being held constant, the average number of entrants is higher when group size is large.

- *Result 3: Group size impacts positively on the number of entrants and entry rates. Larger is the group, the highest the number of entrants or entry rate.*

Empirical evidence for this result is the following. Table 3 indicates that, on average, number of entrants is 8.91 for snowball treatment when $n = 24$ and 8.61 for linear MEG when $n = 24$ (recall that number of entrants predicted by MSNE is 7.64 when $n = 12$ and 7.30 when $n = 24$). Non parametric statistics indicate that the number of entrants is indeed significantly higher for both technologies when group size is to be large (Wilcoxon matched pairs signed-rank tests gave the same statistics for both technologies, i.e. $Z = -2.023$ ; $p = 0.0431$**) under the INC condition. Pooled data for snowball when group size is large indicate also a significant difference with MSNE entry rate (Mann Whitney Wilcoxon rank sum test, $Z = -4.042$, $p = 0.001$***) as for linear MEG (idem, $Z = -2.795$, $p = 0.0052$***).
The regression given previously in table 6 indicates clearly that size also plays a major role in coordination process for individuals, suggesting decreasing propensity to enter as size grows. Such a empirical result is in line with theoretical predictions, as it was pointed above.
When groups are large, coordination is more difficult to achieve and this suggests more deviation around a given equilibrium. Concerning theoretical predictions, if participants play PSNE, there should not be any deviation from period to the other, and dispersion around Nash Equilibriums should be zero. But theoretical predictions based on MSNE concept indicate that standard deviation should be 35% higher when groups are large compared to small groups (see above). In fact, at the aggregate level, standard deviations that are observed in our experimental data are very close theoretical predictions obtained with MSNE (see table 1). Standard deviation is 45.6% higher for snowball MEG when $n = 24$ compared to n=12, and only but 20% higher for linear MEG.

### *4.2 Individual behavior*

The goal of this section is to check wether or not participants play at the individual level Pure Strategy Nash Equilibrium or Mixed Strategy Nash Equilibrium. At the aggregate level, MSNE and PSNE organize quite well the data about entry rate, thus being a very common result in the experimental literature related to MEG. But it is also observed that, at the individual level, very few subjects play pure or mixed strategy Nash equilibriums (See among others, Rapoport, 1995 ; Sundali et al., 1995 ; Erev & Rapoport, 1998).
As it is noted in Rapoport (1995), if all the $n$ agents adhere to the symmetric mixed strategy Nash equilibrium, the distribution of number of entrants should conform to binomial law where the expected number of entrants is $np$ and standard deviation is $\sqrt{\left(\frac{c-1}{n-1}\right)\left(1-\left(\frac{c-1}{n-1}\right)\right)n}$. If all agents adhere to the asymmetric Pure strategy Nash equilibrium, standard deviation of the number of entrants should of course be zero.

We compute the between-subjects standard deviation about the number of entries per individual. If subjects play MSNE, then the expected number of entries for a given agent for each treatment iterated 20 times should be respectivly for $n = 12$ $\left(\frac{7}{11}\right) 20 = 12.73$ and for similar reason for $n = 24$ should be $\left(\frac{7}{23}\right) 20 = 6.09$. The following table gives the average number of entries per treatment and subsequent standard deviations, recalling levels given by MSNE theoretical predictions.

Table 7: Comparison between MSNE theoretical predictions and observed number of entries per subject

| Treatment | Linear MEG | | Snowball MEG | |
|---|---|---|---|---|
| | $n = 12$ | $n = 24$ | $n = 12$ | $n = 24$ |
| expected number of entries (MSNE) | 12.73 | 6.09 | 12.73 | 6.09 |
| expected standard deviation (MSNE) | (1.67) | (2.25) | (1.67) | (2.25) |
| observed number of entries | 13.15 | 7.18 | 12.81 | 7.43 |
| observed standard deviation | (4.94) | (7.08) | (5.33) | (5.50) |

A statistical test is useless to observe that (between-subjects) standard deviations are always larger than predicted ones, such a result being in line with previous experimental results about this game (see Erev & Rapoport, 1998 for instance).
This reveals that equilibrium predictions at the individual level explain quite poorly the experimental data. To investigate more precisely this issue, it is possible to check possible behaviors that are or not in line with PSNE or MSNE. If an agent adhere to MSNE, he should display at the individual level at least on average a number of entries that are in line with theoretical predictions, i.e. should reveal a decrease from 13 entries to 6 entries in INC condition and the reverse sequence for DEC condition. If another agent adhere to Asymmetric PSNE, he should either always enter or never enter,whatever group size is, since PSNE is theoretically not affected by group size. Consequently, the total number of entries for such an agent should be around 40 or around 0 (assuming a certain level of error).
Regarding experimental data, such behaviors are barely revealed. A strong criteria for assessing the adequacy of PSNE is to consider that a given individual should be consistent within a condition (i.e. "always enter" whatever group size or "never enter" whatever group size). The frequency of subjects who always enter or never enter in linear MEG is near to be the same, around 1.25%. In the case of Snowball MEG, the frequency of subjects who always enter[8] whatever group size equals 14.1%. The frequency of subjects who never enter is 54.6%, this last result being easily explained by loss aversion.
Moreover, in order to qualify these parametric results, as it is pointed by Erev et al. (2010), one key experimental result in such Market Entry Game is the high sensitivity of subjects to forgone payoffs. To illustrate that, we compute the correlation between the probability of repeating the same choice as in previous period (1 for repetition, 0 otherwise) to previous obtained payoff and to previous forgone payoff. The absolute correlations are 0.0382 for obtained payoff and 0.1106 for forgone payoff. The same observation applies for

[8] We consider that a particular subject "always enter" if the frequency of entry is equal or higher than 80% (i.e. total number of entries in a given treatment is higher than 15 among the 20 possible).

both technologies, but the sensitivity seems to be higher for linear MEG, as table 8 below reports.

Table 8. Absolute correlations between probability of repetition and payoffs

| | variable | Probability of having $\delta_i^{t-1} = \delta_i^t$ for subject $i$ |
|---|---|---|
| Snowball MEG | $\pi_i^{t-1}$ | 0.037 |
| | $\overline{\pi_i^{t-1}}$ | 0.117 |
| Linear MEG | $\pi_i^{t-1}$ | 0.021 |
| | $\overline{\pi_i^{t-1}}$ | 0.134 |

NB: $\pi_i^{t-1}$ is obtained payoff at last period, $\overline{\pi_i^{t-1}}$ is the forgone payoff for last period

Another point relates to alternation rate exhibited by participants. Alternation could be explained by learning, but also by reactions an individual has when he gets information about past actions of other players. In our setup, participants obtain at the end of each period aggregate entry rate and were perfectly aware about the payoff structure. Moreover, at period $t$, participants obtained information about past entry rates for periods going from 1 to $t-1$. Alternation rate is defined as the number of actual changes in choice from one period to the other compared to the total changes that are possible for a subject. For instance, keeping in mind that subjects are confronted to binary choices, a given subject that should repeat 20 times a given situation of choice could at most make 19 alternations. A first result is that, on average, alternation rate is around 0.25, i.e. the representative subject that could change 20 times from current period to the immediate next one, change 5 times on average and repeats 15 times the same choice. This result is in line with previous results on linear MEG (see for instance Erev et al., 2010). The following table gives summary statistics about alternation rate for each treatment.

Table 9. Average Alternation Rate (s.d.) per Treatment and Group Size

| Congestion Technology<br>group size | snowball | linear |
|---|---|---|
| $n = 12$ | 0.28 | 0.27 |
| | (0.20) | (0.17) |
| $n = 24$ | 0.26 | 0.16 |
| | (0.19) | (0.16) |

There is no significant difference between snowball MEG and linear MEG when group size is low, but in linear MEG, alternation rate decreases when group size is to be increased, contrary to snowball MEG where it remains roughly the same. A non-parametric Wilcoxon Mann-Whitney sign-rank test indicates that alternation rate is higher for snowball MEG played by 24 participants compared to linear MEG with the same group size ($Z = 5.043$ ; $p = 0.000$***). Such profile regarding alternation rate for snowball MEG could also be observed in the following figure (see figure 7). We observe than 36% of alternation rates revealed by participants are less than 6% for linear MEG, which represent the highest frequency for such rates that lie between 0 and a maximum of 0.63. For Snowball MEG, the highest frequency is obtained with AR between 0.31 and 0.37 (22,5%) and the frequency for lowest AR (less than 6%) is only around 20%. The maximum AR is 68.4% in this situation.

We observe than 36% of alternation rates revealed by participants are less than 6% for linear MEG, which represent the highest frequency for such rates that lie between 0 and a maximum of 0.63. For Snowball MEG, the highest frequency is obtained with AR between 0.31 and 0.37 (22,5%) and the frequency for lowest AR (less than 6%) is only around 20%. The maximum AR is 68.4% in this situation.

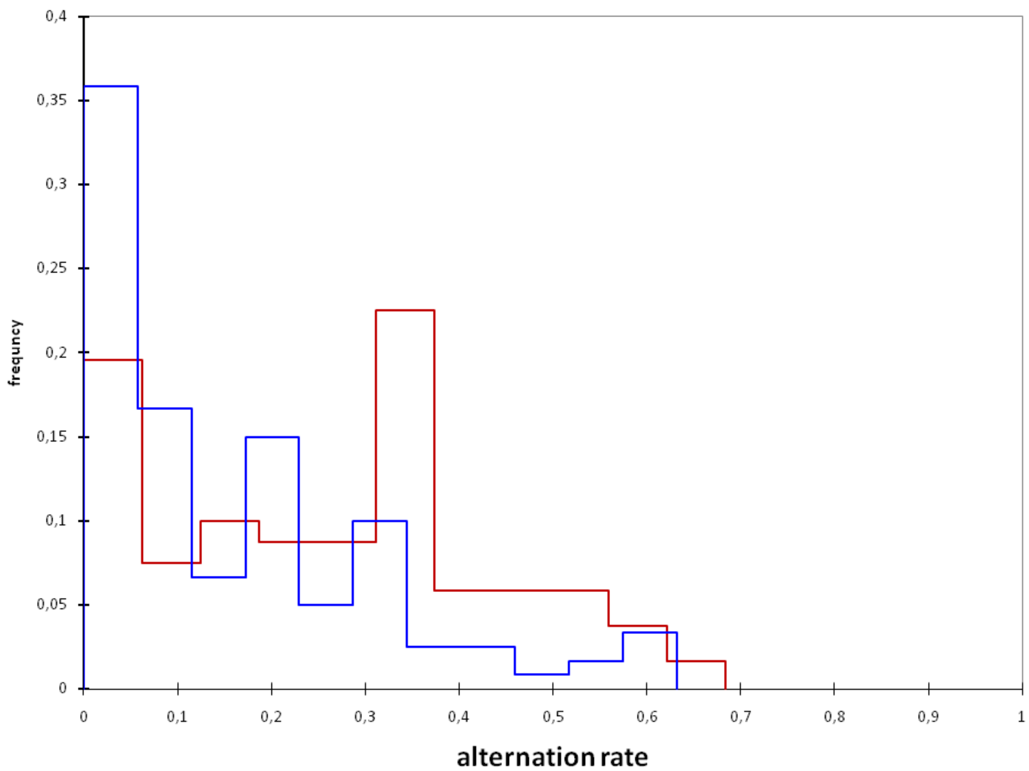


Figure 7. Histogram of Alternation Rate for Snowball and linear MEG ($n = 24$) NB : Blue line corresponds to Linear MEG, red line to Snowball MEG

A parametrical analysis can give more support to the fact that switching from one period to the next is more sensitive to forgone payoffs than to obtained payoff. A Probit regression analysis where the explained variable is the decision to switch (=1 when a given participant change binary decision in $t$ from 0 to 1 or from 1 to 0) is given in the next table (please see table 10), where the first column gives the explanatory variables, the second one the estimated coefficients and the last one reports marginal effects of each explanatory variable.

Table 10. Estimates of a Probit regression model reporting marginal effects about the probability to switch (pooled data)

| Explanatory variable | coeff (st. error) | dF/dx |
|---|---|---|
| Order (=1 if INC condition) | 0.060 | 0.018 |
| | (0.030) | (0.009) |
| Snow[1] (=1 if Snowball MEG) | 0.139*** | 0.042 |
| | (0.030) | (0.009) |
| BigSize[1] (=1 if $n = 24$) | -0.103*** | -0.032 |
| | (0.013) | (0.008) |
| $\lambda_i^{risky}$ | -0.028** | -0.009 |
| | (0.038) | (0.004) |
| $\pi_i^{t-1}$ | -0.0003*** | -0.0001 |
| | (0.000) | (0.000) |
| $\overline{\pi_i^{t-1}}$ | 0.001*** | 0.0003 |
| | (0.000) | (0.000) |
| constant | -0.826*** | |
| | (0.048) | |
| obs. | 12616 | |
| number of subjects | 332 | |
| Pseudo R2 | 0.0183 | |

[1] : $dF/dx$ is for discrete change of dummy variable from 0 to 1

Results of the regression analysis indicate that probability to switch tend to be higher in the snowball MEG environment and lower for large groups, revealing the highest difficulty to coordinate and the propensity to maintain stable decisions. Loss aversion tend to lower the probability to modify choice, as past obtained payoffs.for evident reason, as increasing forgone payoff tend to increase the probability of switching[9]. The marginal effect of forgone payoff is here three time higher on average that the marginal effect of obtained payoff, indicated a strong sensitivity of participants to forgone payoffs in the switching decision.

## 5 Concluding comments

The aim of our experiment was to observe whether or not individual behavior in a traffic congestion game is to be changed due to sharp increase in transport cost compared to a more usual linear form. To this aim, we build an experiment where a snowball congestion game was to be compared to the usual Market Entry Game (MEG), where congestion cost is to be linear. We conjecture that potential huge travel costs could have a detrimental effect on observed entry rate on road compared to theoretical level predicted by Nash equilibrium if loss aversion is to considered. To our surprise, such a major difference does not exist, since no significant difference between experimental entry rates or experimental efficiency levels is to be observed throughout different congestion technologies, that consist either to implement a linear or a quadratic travel cost function for users. Moreover, as in

[9]A Panel Probit Analysis with Random effects with the same variables gives very similar results, with a noticeable exception about loss aversion, that fails to explain significantly the probability to switch.

the usual MEG, participants succeed -at an aggregate level- to coordinate repeatedly and quite successfully around Nash Equilibriums. Nevertheless, at the individual level, things are more complex, as often. First, if Nash equilibrium is quite successful at a macroscopic level, a more detailed analysis about individual behavior shows huge deviations from theoretical predictions, such being also well underlined in past experimental studies about Linear MEG. Last but not least, when it is impossible to find significant differences regarding aggregate behavior in Snowball MEG compared to linear MEG, at the individual level, deviations tend to be more important in Snowball Game, such deviations being more drastically important when group size is to be increased. Another important result relates to size effect: We observe that deviation from equilibrium tends to increase when group size is to be higher, even at the macroscopic level, enhancing the difficult coordination process when groups become larger. This size effect, which is particularly strong, combines itself with the improved difficulty of coordination for agents when they could face snowball congestion costs. This suggests that the number of road users that should interact in real-life situations could be a critical aspect of the coordination process, as well as an essential component for designing policies aiming to solve congestion problems by implementing for instance road-pricing schemes or real-time information providing tools.

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