Gulf Coast Research Center for Evacuation and Transportation Resiliency

LSU / UNO University Transportation Center

AN INTEGRATED APPROACH TO MODELING EVACUATION BEHAVIOR: HYPERBOLIC DISCOUNTING AND PEER EFFECTS

Final Report

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GULF COAST RESEARCH CENTER FOR EVACUATION AND TRANSPORTATION RESILIENCY

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The first part of this research explores the behavior of the naïve or myopic agent in deciding whether to perform a mandatory task whose cost is immediate but reward received only in the future. Following the literature for hyperbolic discounting we say that a player is naïve if her inter-temporal preference for whether to complete an assigned task is represented by the Phelps and Pollack's hyperbolic discounting utility model. We show that a naïve agent, whose present bias is below a certain game-dependant bound, is meant to complete the task in the last period. This bound offers two new insights about the naive player. First, "not all naïve players are equal" in that the long run discount factor decides the degree of naivety sufficient to procrastinate. Secondly, this shows that the range of the payoff structure plays a role in favoring procrastinating behavior. Finally, an application of naive hyperbolic discounting for an evacuation model is constructed.

The peer effects research is concerned with testing the hypothesis that an agent's decision of whether to evacuate during a hurricane is influenced by the fear propensity of his or her peers. To explore this human aspect of an evacuation, a simple random utility model is set up where the utility of the "agent who is not scared" is allowed to depend on the fear propensity of the group she identifies with. The resulting binary choice model derived contains a real key parameter measuring the peer effect. Using data from Hurricane Floyd, we estimate that a positive peer effect exists in the sense that the larger the fear propensity of the peer group, the more attractive an evacuation. This finding suggests that policies aimed at creating strong awareness of hurricane dangers before the hurricane season can have a substantial effect on the population's evacuation rate via their multiplying effects.

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B. Disclaimer

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Executive Summary

- Our goal is develop an integrated approach to understanding the evacuation decision of individuals in the face of natural disasters. The study focuses on two behavioral phenomena that have increasingly important in the last decade: *hyperbolic discounting* and *peer effects*.

- Hyperbolic discounting introduces a strong preference for present utility or present bias, and is particularly relevant for tasks where the reward may be in the present and costs are incurred in the future (or vice-versa). An example of this is quitting smoking: the enjoyment of current consumption prolongs quitting despite the future health costs associated with the habit. The evacuation decision also has the similar characteristics: costs to evacuate are incurred today, while the benefits of safety and survival are only received in the future when the event is over. Peer effects suggest that while individuals have personal beliefs about decisions, they are influenced by others (social learning), which according to anecdotal evidence plays a key role in the evacuation decision. Due to lack of data on time preferences of individuals, the relationship between hyperbolic discounting and evacuation is studied theoretically, while peer effects (in terms of fear) are investigated empirically using data from Hurricane Floyd.

- The model of hyperbolic discounting considers a finite horizon decision problem with an additive utility function. The model incorporates a long run discount factor δ and a parameter for immediate gratification denoted by β. Agents earn v_t a reward for completion of the task in period t while c_t indicates the cost for performing the task in period t.

- Time consistent players can be thought of as the control group for our analysis since they always value well-being equally regardless of the point in time they are asked to make the decision. In other words they do not have a present bias. We consider two types of individuals who have a present bias, i.e., exhibit self-control problems: naïve or sophisticated agents. Naïve players do not accurately predict their self-control problem. Sophisticated players realize they will not act how they would like to in the future (i.e., are aware of their self control problem), and change their current actions accordingly. An example in the report illustrates the difference between all three types. The focus of this study is on the naïve players.

- We find that the long run discount determines the degree of naivety sufficient to procrastinate and the effect of impatience on procrastination is determined by the "maximum cost per excess reward" ratio. We show that procrastination is nurtured by low payoff variability. Finally, when the percentage increase in the cost in the last period is less than the first period then a naïve player with a reasonable long run discount will never be time consistent.
- In the peer effects model, we include the fear level of the peer group into the cost-benefit analysis for two reasons: peers' fear may act as risk perception for those with limited knowledge of hurricanes' potential damage and individuals may simply value social

mimicking because of its utility. We find there is a positive peer effect, where the larger the fear propensity of the peer group, the more attractive the evacuation.

- The data was collected in January 1999 from a random sample of households from the North Carolina Coastal region, and again after Hurricane Floyd in early 2000. It includes information on attitudes about safety during hurricane watch, whether they evacuated, and socioeconomic characteristics about the household.

- In the empirical model the decision to evacuate depends on the individual's costs and benefits as well as the behavior of their peers. The first model concentrates on the evacuation decision of an agent who is not scared and who makes the evacuation decision based on own attributes and peer effects. The estimator for this is derived from the smoothed maximum score estimator introduced by Horowitz (1992). The second model examines the same decision and uses a Maximum Likelihood estimation procedure while specifying the evacuation equation of the scared agent as well to address a potential sample selection problem that may exist in the first model.

- We find that for an individual who is not scared of hurricanes: (*i*) receiving an evacuation order increases the probability of evacuating, (*ii*) an additional year of schooling increases the probability of evacuating, (*iii*) owning a house decreases the probability of evacuating, (*iv*) living in a mobile home increases the probability of evacuating, (*v*) being one year older decreases the probability of evacuating, (*vi*) being married increases the probability of evacuating, (*vii*) being white increases the probability of evacuating, (*viii*) being a female increases the probability of evacuating, and (*ix*) living an additional year in the region decreases the probability of evacuating. Interestingly, a 10% increase in the population of scared individuals in an individual's group has the same effect on the probability of evacuating as an additional year of schooling. In terms of policy our research suggests that increasing awareness about the danger from hurricanes using various channels can have a substantial effect on the number of evacuees; peer effects can amplify the impact of information provided by policy makers.

An Integrated Approach to Modeling Evacuation Behavior: *Hyperbolic Discounting and Peer Effects*

ABSTRACT:

A spate of recent hurricanes and other natural disasters have drawn a lot of attention to the evacuation decision of individuals. Here we focus on evacuation models that incorporate two economic phenomena that seem to be increasingly important in explaining human behavior: *hyperbolic discounting* and *peer effects*.

The first part of this research explores the behavior of the naïve or myopic agent in deciding whether to perform a mandatory task whose cost is immediate but reward received only in the future. Following the literature for hyperbolic discounting, we say that a player is naïve if her inter-temporal preference for whether to complete an assigned task is represented by the Phelps and Pollack's hyperbolic discounting utility model. We show that a naïve agent, whose present bias is below a certain game-dependant bound, is meant to complete the task in the last period. This bound offers two new insights about the naïve player. First, "not all naïve players are equal" in that the long run discount factor decides the degree of naivety sufficient to procrastinate. Secondly, this shows that the range of the payoff structure plays a role in favoring procrastinating behavior. Finally, an application of naive hyperbolic discounting for an evacuation model is constructed.

The peer effects research is concerned with testing the hypothesis that an agent's decision of whether to evacuate during a hurricane is influenced by the fear propensity of his or her peers. To explore this human aspect of an evacuation, a simple random utility model is set up where the utility of the "agent who is not scared" is allowed to depend on the fear propensity of the group she identifies with. The resulting binary choice model derived contains a real key parameter measuring the peer effect. Using data from Hurricane Floyd, we estimate that a positive peer effect exists in the sense that the larger the fear propensity of the peer group, the more attractive an evacuation. This finding suggests that policies aimed at creating strong awareness of hurricane dangers before the hurricane season can have a substantial effect on the population's evacuation rate via their multiplying effects.

1. Introduction

A spate of recent hurricanes and other natural disasters have drawn a lot of attention to the evacuation decision of individuals. This is a complex decision that depends on the characteristics of an individual, their specific location and community as well as available resources and infrastructure facilities. A better understanding of this decision will help policy makers and those involved in transportation planning and management to design better evacuation plans. This research may be seen as a first step to developing an integrated approach that incorporates both economic and non-economic variables for understanding the evacuation decision. Typically models of evacuation behavior developed by economists often tend to ignore storm and traffic related data, while non economists often tend to ignore economic issues like risk attitudes. As a first step, we focus on evacuation models that incorporate two economic phenomena that seem to be increasingly important in explaining human behavior: *hyperbolic discounting* and *peer effects*.

Economists generally assume that individuals have time consistent preferences, i.e., individuals' relative preferences for utility between two different dates is the same no matter when he/she is asked. However, this modeling of preferences is not always accurate since many individuals prefer instant gratification to waiting, and thus this rationale should be incorporated into economic models. The easiest way to think of this is the fact that most of us procrastinate doing unpleasant tasks or chores at home. Hyperbolic discounting captures this notion by introducing a strong present bias and is particularly relevant for tasks where the rewards may be in the present and costs have to be incurred in the future or vice versa. For instance, smoking provides rewards today while costs are incurred in the future which often manifests itself in the tendency to postpone quitting. The same is often true for losing weight. Getting an education imposes costs today while the rewards are in the future. The decision to evacuate has the same flavor. All the costs associated with such a decision have to be incurred today[1] while rewards of being safe and enjoying the same quality of life are only in the future after storm blows and all the chaos blows over. Hence it is important to understand how individuals with different notions of discounting will behave when faced with a decision to evacuate.

The idea of peer effects in this Internet driven society is not difficult to understand or explain. In recent years there is a large body of literature in a number of disciplines ranging from economics and marketing, to sociology and psychology which argues that our decision are often affected by our social networks and peers. In other words, while we have our own beliefs about what decision to make or what to chose, we often learn from others (social learning) and our final decision is influenced by both. In fact, there is a great deal of anecdotal evidence which suggests that peer effects are very important in the decision to evacuate. The ideal model would incorporate both features simultaneously. However due to lack of data on of the present bias of individuals we follow a two-part strategy. The relationship between hyperbolic discounting and evacuation is studied theoretically, while the peer effects manifested in the form of "fear" is investigated empirically using data from Hurricane Floyd. For both problems we provide results that are of a more general nature, i.e., they may be construed as basic research. They contribute to knowledge in the field. We then provide results that are more applied in nature in the sense that they pertain directly to the problem of evacuation and rely on the basic knowledge

[1] Evacuation costs are not just monetary. They usually require meticulous planning and involve a great deal of tedium.

developed. Finally, note that results from both investigations suggest that this is an important topic that deserves further exploration. In particular, it is important to develop models that simultaneously include both the phenomena mentioned above. This is especially important since peers can affect discount factors.

The rest of this report is organized as follows. Section 2 outlines the theoretical and provides results. Section deals with empirical model and results. Section 4 discusses future research and funding possibilities.

2. Hyperbolic Discounting and the Evacuation Decision

In this section we focus on the theory model that focuses on hyperbolic discounting. First we present the theory model followed by a discussion of the main findings.

2.1 Model Setup

Economists generally assume that individuals have time consistent preferences, i.e., individuals' relative preferences for utility between two different dates is the same no matter when he/she is asked. However, this modeling of preferences is not always accurate since many individuals prefer instant gratification to waiting, and thus this rationale should be incorporated into economic models.[2] This can easily lead to inconsistencies in preferences. To illustrate this using monetary values consider the following illustration provided by Kirby and Herrnstein (1995) which can be summarized as follows: most agents prefer 100 Dollars today over 110 Dollars next year but those same agents claim to prefer 110 Dollars in 5 years over 100 Dollars in 4 years.

An increasingly popular technique that is being implemented now is a modification of the exponential discounting, with the following *hyperbolic utility function* (Phelps and Pollack (1968), Laibson 1994, 1997; Fischer 1997, O'Donoghue and Rabin 1997)[3]:

$$U_t(u_t, u_{t+1}, \ldots, u_T) = \delta^t u_t + \beta \sum\nolimits^{T}_{\tau=t+1} \delta^{\tau} u_{\tau}. \qquad (1)$$

In the above equation, δ and β are between 0 and 1.[4] Parameter β is the measure of an individual's preference for immediate gratification, and δ is the discount factor for long-run impatience (and is time consistent). Here we follow the formulation of Phelps and Pollack (1968) since this is the most popular one in the literature. Notice that for $\beta = 1$ we are in the world of exponential utility (Samuelson, 1937). To elaborate this further, assume that the utility function is additively separable. Further assume that the agent has T periods to decide when to complete a mandatory task whose cost is incurred in the completion period while the reward is obtained in the future. Then the time t utility function of the agent who plans to perform the required task at period $\tau \geq t$ has a utility function that satisfies

$$W_t(\tau) = \{\beta\delta^{T+1}v_t - \delta^t c_t\}1_{\tau=t} + \{\ \beta(\delta^{T+1}v_\tau - \delta^\tau c_\tau\ \}1_{\tau>t} \qquad (2)$$

where v_t is the reward for completion in period t while c_t indicates the cost for performing in period t. The same explanation holds for the variables when τ is the superscript or subscript and 1 is just an indicator to capture the relevant period.

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[2] Another common example of time inconsistent preferences is: if asked on Monday, an individual would claim that having fun on Friday and Saturday were equally important, but when asked on Friday, having fun that day would be much more important than having fun Saturday.

[3]The literature also considers some other types of discount functions which are similar to the one used above with marginal differences based on the application in question. See for instance Ainslie (1975), Herrnstein and Mazur (1987), Loewenstein and Prelec (1992) to model problems where agents displaying this discount "myopia" must solve an intertemporal problem.

[4] This utility function has been has been used extensively for explaining various time inconsistent choices in reality, like low U.S household saving rate (Laibson, 1998), criminality choices (Lee, 2005) and drop-out rate of teenagers (Oroupoukos, 2002).

The problem of dynamic inconsistencies leading to procrastination for a future reward immediate cost game can be understood by adopting (2) because $\beta < 1$ may yield reversals in the agent preferences simply due to the passage of time. A *self-control problem* in this framework occurs *when a person wishes to behave a certain way in the future, but behaves differently when the future arrives* (O'Donoghue and Rabin 2000). One example of this is of a smoker who wants to quit, but says he/she will quit tomorrow instead of today. When tomorrow arrives, he/she continues to put off quitting because of the utility they gain from smoking today. There are two different types of individuals who exhibit self-control problems: naïve or sophisticated. *Naïve* individuals *do not accurately predict their self-control problem,* while *sophisticated* individuals *realize that they will not act how they would like in the future, and change their current actions accordingly*. We also refer to these individuals as the *naifs*. The *time consistent players* always *value well-being equally regardless of when they are asked*. They do not have self-control problems, and in a sense can be thought of as the control group for our analysis.

In this paper, we are interested in the naif agent who has a finite number of periods to decide whether to complete a task whose action has an immediate cost but reward is obtained in the future only. To the best of our knowledge some, there are three interesting issues that have not yet been addressed by the literature. First, the link between the short run discount factor and the long run discount factor. The literature (Rabin 1999) has tackled the analysis by scaling the payoffs to focus on the present bias ignoring the exact interaction long run and short run discount factors. This is important because a naif hyperbolic discounter is characterized by both her present bias but also her long run discount factor. Indeed, we show that in general the role of the long run discount in favoring procrastination is ambiguous depending on what we may call the "cost-reward ratio" of the game and the horizon. Secondly, we study the role of the payoff structure in inducing procrastination. We establish that low ranges for the cost and reward schedule promotes continuous postponing in an asymmetric manner in that the naif is more sensitive to the cost variation. Finally, we show that the effective completion period chosen by a naif agent reveals information about her present bias i.e. short run discount factor which with available data would allow for the construction of consistent estimator of the short run discount factor.

2.2 Some General Results about Hyperbolic Discounting

The focus of our results is on the naïve players since they are the ones who will have the greatest difficulty in evacuating. However later in this section we use an example to illustrate the difference between these players, those who are time inconsistent, but sophisticated and individuals who do not use hyperbolic discounting. We will first begin by presenting our general results on hyperbolic discounting and naïve players and then proceed to deal with the evacuation scenario.

Our first result is a lemma that proves very useful for subsequent results. It says that the sequential problems faced by the naifs can be resolved only by comparing the "present deal" to the "best deal of the future." This eliminates the need for period by period comparison and simplifies things by requiring comparison of only two payoffs.

Before describing our next result we need to define some notation. Let $\max_{t\leq T} v_t = v^h$ and $\min_{t\leq T} v_t = v^l$. Similarly, let $\max_{t\leq T} c_t = c^h$ and $\min_{t\leq T} c_t = c^l$. We now state our next result.

Proposition 1: *For every game with $c >> 0$ there exists a threshold factor $\beta_* \in (0, 1]$ such that a naïf whose short run discount is strictly smaller than β_* will complete the action at time T, where $\beta_* = c^l/(\delta^{1-T}c^h+\delta v^h - v^h)$.*

This proposition follows from the first lemma. Basically, it says that if the cost of completing the task is strictly positive for all periods, then a naif whose short run discount factor is below a certain bound, function of the payoffs extremum and that very agent's long run discount, then such an agent will complete the task at the end. This result suggests that low variation cost and reward structures favor procrastination. One explanation is that under immediate cost but future reward, a payoff structure with low variability will, in each period, give a naif good reason to postpone completion as the future offers a cost advantage over the present. Yet, rearranging β_* shows that, keeping the long run factor and minimum cost constant, the variation of the cost and reward plays an asymmetric role in that the variation of the cost structure matters more than that of the reward sequence. In other words, a naif late completion is more sensitive to the cost variation.[5]

This proposition is also important to understand perpetual postponing of naif players because it highlights the relevance of the naif player's impatience in deciding about the degree of naivety sufficient to procrastinate. In other words "not all naïf players are equal" when facing a game with immediate cost and future reward. Indeed, in general it is not clear whether a higher long run discount is more conducive to exhibiting time inconsistent decisions. Examining the bound of games for which the reward is not constant is useful for understanding why the impact the long run discount is ambiguous. In that case, it is easy to show that the bound will be increasing on $(0, \delta_*)$ and decreasing on (δ_*, ∞) where $\delta_* = (T - 1c^h/(v^h - v^l))^{1/T}$. It follows that whether impatience promotes late completion for a naif is determined by what can be viewed as a form of maximum cost per excess reward. However, there are some classes of games for which a unambiguous response is possible. For instance, if the reward and cost are identical in each period then the bound becomes δ^{T-1} so that clearly patience promotes procrastination. Also, if the reward is the same for all periods then we can easily see that patience promotes procrastination.

Two corollaries of this proposition then provide the bounds and also sufficient conditions for the existence of procrastinating behavior. Note that since we lack data we will not go into the details of constructing a consistent estimator. Instead we now move to of illustration of evacuation behavior.

2.3 Results Pertaining to Evacuation Behavior

Let T = {1, 2, 3} be the time periods during which an agent may evacuate. For simplicity we assume that the evacuation order is compulsory so that the resident cannot stay beyond $t = 3$. Let $\{v, c_t\}_{t=1,2,3}$ be the sequence of marginal benefits and costs of evacuating in each time period. The constant marginal benefit of evacuating can be viewed as the value that economic agents attached to safety or of life.[6] Finally, we assume that the marginal cost of evacuation is strictly positive and increasing as time passes. The monotonicity of the cost sequence stems from the

[5] It is interesting to contrast this finding to Rabin and O'Donoughue (2008) which highlights the relevance in the cost structure for explaining the procrastinating propensity of a naif who may complete a two stage project (under infinite horizon) in that when the cost is uneven (ie uneven allocation between the starting cost and concluding cost) the highest cost acts as a hurdle on the naif player preventing completion.

[6] The mechanism by which v is generated under uncertainty (Bayesian expectations) is irrelevant as well as change in the value of v provided the agent uses that same updated reward in each optimization period.

implicit assumption that the cost of evacuating comprises the alternate housing cost(for example hotel costs which adjusts rapidly to heightened demand) and transportation cost (driving cost where distance required to find a place to stay is increasing in the time period as closer hotels are exhausted first). One important assumption, which seems appropriate in this context, is that the cost of the evacuation is immediate (incurred in the period where the agent leaves the house) but the marginal benefit is received only in the future which we take to be t = 4. We note W_t be the inter-temporal utility of the agent in period t. Following Rabin and O'Donoughe (1999) we posit a simple value function, separable in benefit and cost, which as a function of the planned evacuation period τ is given as below:

$$W_t(\tau) = \{\beta\delta^4 v_t - \delta^t c_t\}1_{\tau=t} + \{\ \beta(\delta^4 v_\tau - \delta^\tau c_\tau\ \}1_{\tau>t}$$

where $0 < \beta < 1$ and $0 < \delta < 1$. Finally, we adopt the convention that the evacuation is completed in the current period if generating the same level of utility as some future periods.

The naïve agent maximizes her inter-temporal utility in the first period by finding the value that maximizes the argument, i.e. which provides τ (1) = $argmax_{\tau\geq 1}$ $W_1(\tau)$ as the optimal planned time to evacuate. If $\tau(1) > 1$, the agent will reconsider the evacuation in the second period yielding $\tau(2)$ = $argmax_{\tau\geq 2}$ $W_2(\tau)$. The present bias of a naif opens the possibility (but not the guarantee) to display time inconsistent choices. Especially we seek to understand the exact role of the present bias and impatience to rationalize the outcome τ (1) = 2 and$\tau(2)$ = 3 i.e. the inhabitant initially decides to evacuate in the second period but eventually evacuates during the deadline. Before providing the general solution for such a problem, it is instructive to understand the problem of having a naif by examining a simple numerical example.

Example: Consider 3 different players. Suppose the marginal benefit of evacuating is 1000 and the cost vector is c = (1, 1.1, 1.3) in the three periods respectively for all players. We norm the impatience of all the players to 1 and assume that $(\beta_1, \beta_2, \beta_3)$ = (1, 0:9, 0:8) respectively for the three players. The outcomes for each player are provided as below:

case $\beta = 1$	period 1 utility	period 2 utility	period 3 utility
t=1	999.000	998.900	998.67
t=2	.	998.900	998.669
case β = 0.9	.	.	
t=1	899.000	899.010	899.800
t=2	.	898.900	898.802
case β = 0.8	.	.	
t=1	799.000	799.120	798.940
t=2	.	798.900	798.935

TABLE 1

(i) **Player 1:** She is the time consistent player since her utility function is just the standard exponential utility function with β=1. Using the above equation for utility, it can be shown that she evacuates in the first period.

(*ii*) **Player 2:** The second player has a present bias, but behaves like a sophisticated player. It can be verified that at t = 1, she decides to postpone evacuating till period 2. When period 2 arrives, it is still optimal for her to evacuate and so she does. Thus she is time consistent.

(*iii*) **Player 3:** In the first period she decides to evacuate in period 2. Yet at t = 2 she does not evacuate since t = 3 offers higher utility when computed at t = 2. Thus this player procrastinates and is time inconsistent.

We are now in a position to state our main result for this setup.

Proposition 2: *Let (β,δ) describe a naïve player's preferences. Furthermore, suppose that $0 < c_1 < c_2 < c_3$ and let $\delta_* = c_2/c_3$.*

(i) There exists $\beta_1^* \in (0, 1)$ such that the naif evacuates in the first period if and only if $\beta \geq \beta_1^*$. Moreover $\beta_1^* = c_1/\delta c_2$ if $\delta \geq \delta_*$ and $\beta_1^* = c_1/\delta^2 c_3$ otherwise.

(ii) There exists β_2^* such that conditional on having not evacuated in the first period, the naif departs in the second period if and only if $\beta \geq \beta_2^*$. Moreover, $\beta_2^* = c_2/\delta c_3$.

From the above proposition we also obtain the following corollary.

Corollary 1:

(i) Under $\delta \geq \delta*$

$$(\tau(1), \tau(2)) = (2,3) \iff \beta \in (0, \tfrac{1}{\delta} min\{\tfrac{c_1}{c_2}, \tfrac{c_2}{c_3}\})$$

$$(\tau(1), \tau(2)) = (2,2) \iff \tfrac{c_2}{\delta c_3} < \beta < \tfrac{c_1}{\delta c_2}$$

$$(\tau(1), \tau(2)) = (1,\emptyset) \iff \tfrac{c_1}{\delta c_2} < \beta < 1$$

(i) Under $\delta < \delta*$

$$(\tau(1), \tau(2)) = (3,3) \iff \beta \in (0, \tfrac{1}{\delta} min\{\tfrac{c_1}{\delta c_3}, \tfrac{c_2}{c_3}\})$$

$$(\tau(1), \tau(2)) = (3,2) \iff \tfrac{c_2}{\delta c_3} < \beta < \tfrac{c_1}{\delta^2 c_3}$$

$$(\tau(1), \tau(2)) = (1,\emptyset) \iff \tfrac{c_1}{\delta^2 c_3} < \beta < 1$$

Based on these results we can make a few general remarks about such a game. First observe that concerning the optimal planned evacuation of the first period we notice that if $\delta \geq \delta_*$ then the last period can never be chosen while if $\delta < \delta_*$ the second period that is not a possible choice. Second, if $\delta \geq \delta_*$, there is always a level of present bias that would generate a deviation from the original plan. This cutoff value is given by $(1/\delta)$ min $\{c_1/c_2, c_2/c_3\}$. Furthermore, this bound is decreasing in δ implying that patience mitigates present bias' penchant to deviate. Next, if $\delta \geq \delta_*$, a necessary condition on the payoff in order to be consistent for an evacuation in the second period is that the percentage increase in cost between period 2 and 3 exceeds that of between period 1 and 2. Otherwise, a naif planning to evacuate in period 2 will eventually evacuate at the end. Finally, if the previously mentioned cost condition holds then multiplying all the cost by a positive constant has no impact on the effective evacuation period of a naive agent. In other words, it is the relative percentage change in cost that determines the behavior of a naif.

According to our research, the key points concerning a naif hyperbolic discounter who must decide whether to perform an immediate cost-future reward task can be summarized as follows. First, it is the long run discount that decides the degree of naivety sufficient to procrastinate and that the effect of impatience on procrastination is determined by the "maximum cost per excess reward" ratio. Thus, deciding whether the long run discount factor is a "substitute" or "complement" to the short run discount must be analyzed from the perspective of this ratio. Secondly, we learned that procrastination is nurtured by low payoff variability. Finally, according to our evacuation model, in terms of policy it suggests that when the percentage increase in the cost in the last period is less than of the first period then a naif with a reasonable long run discount will never be consistent. However insightful, it is important to remember that these results have been proven only in the context of immediate cost-future reward games under finite horizon. Generalization of those results to other types of games (i.e. immediate reward-future cost for instance) is not warranted as of now but would be an important contribution to the literature on naive players.

3. The Evacuation Decision: Fear Contagion through Peer Effects

This research is concerned with testing from data the hypothesis that an agent's decision of whether to evacuate during a hurricane is influenced by the fear propensity of his or her peers. There is a tacit agreement in the hurricanes literature that the social environment or "peer pressure" is important in shaping one's evacuation choice (see Baker, 1991; Burton et al., 1993; Viscusi, 1995; Perry, 1979; Riad et al., 1999). To the best of our knowledge however the mechanism through which the peer behavior operates has not been explored yet. Understanding how the behavior of the "group" one identifies with shapes her decision of whether to evacuate carries important policy implications. This is because the only practical exogenous change currently performed by the policy maker to influence evacuation has been the mandatory evacuation order. Having another peer effect channel through which a higher evacuation rate can be achieved represents a potential life saving tool. The death toll of Hurricane Katrina for instance is estimated at 1,836 people, a number that could have certainly been lower, had more individuals evacuated (Knabb et al., 2005).

We set up an empirical model to test the conjecture that fear of one's reference group influences the agent who is not in general scared of hurricanes. There are two reasons to include the fear level of the peer group into the cost-benefit analysis of the individual who must decide whether to evacuate. First, the peers' fear may act as risk perception builder for those who have limited knowledge of hurricanes' potential danger. Second, individuals may simply value social mimicking because of the utility this provides (Becker, 1974). That is, the peers' evacuation rate enters the preference of the agent. In that case, the information accumulated via social interactions in the preceding weeks may be used by the individual to gauge the behavior of her reference group. Using data from Hurricane Floyd, we estimate that a positive peer effect exists in the sense that the larger the fear propensity of the peer group, the more attractive the evacuation. This finding suggests that policies aimed at creating strong awareness of hurricanes dangers before the hurricane season can have a substantial effect on the population's evacuation rate. This is due to peer effect which acts as a multiplier on any change to fear in the population.

This paper contributes to the literature about the determinants of a hurricane's evacuation (Irwin and Hurlbert, 1995; Wilmot and Mei, 2004; Whitehead, 2005) and to a lesser extent to the estimation of peer effects for binary choice models (Davezies et al., 2009; Brock and Durlauf, 2007). However, unlike the peer effects literature, our model does not assume that all agents value others actions. Also, the statistical model proposed shares similarities with the treatment models used in econometrics (Rosenbaum and Rubin, 1983) in the sense that fear of hurricanes may be construed as a dichotomous treatment with the peer variable interpretable as a form of "propensity score" (Hirano et al., 2003). Finally, our new estimation technique directly relates to the semiparametric literature for binary choice models (Manski, 1985; Horowitz, 1992).

3.1 Background Literature

There have been three main schools of thought in measuring the influence of the social environment when the agent must decide whether to perform a certain action depending on what is meant by the reference group, the timing of agents' decisions and how much information agents possess. In the first approach the peer group is assumed to be location based, individuals decide simultaneously and have common knowledge about their peers' attributes. In that case, the observed choices for a group collected by the econometrician are assumed to be a Nash equilibrium whenever one exists. This model is realistic for describing social interactions when location forms a natural grouping and if a group size is small so that individuals know each others' attributes well. For instance, (Krauth, 2006) examined the peer effect for smoking at the classroom level and (Harris et al., 2008) at the family level.

The second "Bayesian approach" does not assume common knowledge. Rather, using some easy to observe group's characteristics, the peer behavior is guessed by the agent who is assumed to hold rational expectations. In effect, this turns the peer variable in a binary choice model into a constant for each group. This low variability presents important identification issues as demonstrated by Brock and Durlauf (2007) because the fixed effect in a group may be confounded for the peer effect. Additionally, a drawback of this last approach is to impose a somewhat arbitrary peer variable in the model due to the fact that rational expectations are only rational in the context of the chosen model for the binary decision.

The last approach relies on the recent theoretical work on social networking (Jackson et al., 2006, see) which recognizes that the selection of a reference group for an individual is the fruit of a richer process linking individuals because of their locations but also ethnicities and values to cite a few. For instance, (Bramoullé et al., 2009) provide a spatial econometrics approach to explore the network's consumption effect on the consumption of a secondary school student. However, this last estimation procedure does not apply for a binary choice model.

It is important in general to distinguish between the contextual peer effect and the endogenous peer effect as pointed out by (Manski, 1993). The contextual peer effect is caused by the prevalence of some characteristics in the group. The endogenous peer effect arises whenever the peer’s decisions are taken into account by the individual. Unlike the previous literature whose main intersect is the endogenous peer effect, our peer variable is interpretable as a contextual peer variable. Responding to our question of interest requires addressing two main modeling issues. First, we must decide what defines the reference group for an individual. In our research we assume that the reference group comprises the population sharing some discrete socioeconomic "peer" attributes say Z. Including socioeconomic attributes permits us to model situations where individuals are socially linked beyond their location. This is important since there is both theoretical and empirical evidence that resemblance fosters trust.

Secondly, constructing a choice model for the evacuation decision demands addressing the amount of information possessed by individuals. Basically, we need to make an assumption about how the fear propensity P [s = 1 Z] is measured for the unscared agent. We assume that the unscared agent hold rational expectations. In other words, the distribution of s Z is known to the individual whose "peer" attribute is Z. However, it is important to bear in mind that the distribution in question is not known to the researcher although it can be estimated. We believe that a rational expectation framework offers some objectivity in that it is free of parameterization.

To estimate the resulting model, we are primarily concerned about the weakness of the distributional assumptions and the endogeneity of fear. When fear is exogenous enough to meet a certain restriction generalizing the "treatment ignorablity" condition (Rosenbaum and Rubin, 1983) for the median case, we propose a simple extension of the smoothed maximum score estimator (Horowitz, 1992). When fear is correlated with unobservable drivers of an evacuation, then the previous semiparametric estimation method no longer delivers consistent estimates. This may arise for instance, when common hard to observe factors decide both evacuation and fear, one of which might be the health status of the individual. In econometrics, controlling for the possibility of an endogenous dichotomous variable in the binary choice model requires stringent distributional assumptions. We address the possible endogeneity of fear by using a maximum likelihood approach.

3.2 Data

This data set comes from (Whitehead, 2005). In January 1999 a random sample of households from the North Carolina Coastal region was collected via telephone survey. Respondents provided socioeconomic attributes and were also asked how safe they would feel about a hypothetical hurricane approaching. The key question posed prior to hurricane Floyd is phrased as follows:

*A "**hurricane watch**" means that a hurricane poses a possible threat. If a hurricane watch is announced for this hurricane, how safe would you feel in your home?*
1. not safe at all
2. very safe or somewhat safe.

We define the binary variable Scared of Hurricane Watch denoted by s such that s = 1 if the individual answers that they do not feel safe at all in their home, and s = 0 otherwise.

In September 1999 Hurricane Floyd generated the third largest evacuation in US history (behind Hurricane Gustav and Hurricane Rita, respectively) with mandatory evacuations reaching close to 3 million residents from five states. At peak strength Floyd was a Category 4 hurricane before nearing the East Coast of the United States. Floyd then weakened making landfall in North Carolina as a Category 2 hurricane. It was directly responsible for 57 fatalities. In early 2000 the households from the original survey were re-contacted in order to record their evacuation decisions during Floyd. The table below shows the descriptive statistics of the variables used.

Variable	Obs	Mean	Std Dev	Min	Max
Evacuated	384	0.372	0.484	0	1
Evacuation Order	384	0.190	0.392	0	1
Owns Home	384	0.846	0.361	0	1
Mobile Home	384	0.216	0.412	0	1
Age	364	49.964	17.568	16	97
Married	384	0.669	0.471	0	1
White	384	0.846	0.361	0	1
Female	384	0.619	0.486	0	1
Education	384	3.33	1.514	1	6
Distance to Water	383	9.261	10.576	0	50
Years living in County	383	10.548	11.131	0	76
Risk of Flood	384	0.135	0.342	0	1
Risk of Wind Damage	384	0.317	0.466	0	1
Scared of Hurricane Watch	384	0.203	0.402	0	1

TABLE 2

Note that total number of observations is reasonable in this study. Although, it would be interesting to have some more socio-economic characteristics, this data set contains all the basic ones like age, education and gender. The bottom part of the table contains variables that are important for studying hurricanes. One last thing to note is that 20 percent of the population answered in the affirmative to the hurricane watch question.

3.3 Empirical Model

Let s = {0, 1} be the fear of event E where s = 1 if the agent is scared about the occurrence of the event while s = 0 otherwise. Let y = {0, 1} indicate the choice of the agent when event E occurs with y = 1 if action A is completed while y = 0 otherwise. In the context of our specific problem the event is "hurricane strikes" and the action is "evacuate house". However, we keep this general since this framework may be suitable to other problems. The econometric model partitions the population by its s-type before the event occurs. We then proceed to define the utility of the agent for whom s = 0.

To simplify things we impose an additive form of utility which includes social identifiers and the peer effect by determining the perceived fear propensity of an individual's peer group. The peer group is based on social characteristics. Thus the decision to evacuate depends on the individual's costs and benefits as well as the behavior of their peers. It is also assumed that agents have rational expectations about their fear propensity.[7] It means that they can compute their own fear factor correctly based on those of their peers. While this may not be true in all applications, we believe that in our context it applies possibly since the data covers coastal residents and often from smaller places. Implicitly the rational expectations assumption states that agents have a very high degree of knowledge about each other or high social networking.

Two different econometric specifications are estimated. The first model concentrates purely on the evacuation decision of an agent who is not scared makes an evacuation decision based on own attributes and peer effects. The estimator used is derived from the smoothed maximum score estimator introduced by Horowitz (1992). Essentially it eliminates the need for parameterizing the distribution by imposing a median restriction. The second model uses a Maximum Likelihood estimation procedure and addresses a potential sample selection problem that may exist in the first model by also specifying the evacuation equation of the scared agent. Technical details of the estimation procedures are omitted here but can be found in the technical appendix that follows.

3.4 Results

The initial results of our estimation yield the following key facts. Under *ceteris paribus* conditions, for an individual who is not scared about hurricanes we find that:

- Receiving an evacuation order increases the probability of evacuating
- An additional year of schooling increases the probability of evacuating
- Owing a house decreases the probability of evacuating
- Living in a mobile home increases the probability of evacuating
- Being one year older decreases the probability of evacuating
- Being married increases the probability of evacuating
- Being white increases the probability of evacuating
- Being a female increases the probability of evacuating
- Living an additional year in the region decreases the probability of evacuating

Finally, the estimate for the key peer variable is positive suggesting that a 10% increase in the population of scared individuals in my group (i.e. those living in my county, having the same race, same demographic and wealth profile) has the same effect on the probability of evacuating as an additional year of schooling.

Using our econometric model, we can decompose, the change in the probability of evacuating due to *an exogenous* increase in the probability of being scared about hurricanes in the manner shown below:

Change in the probability of evacuating in the population = ATE+ m×d

[7] This is a standard assumption in the peer effects literature (see Brock and Durlauf, 2007).

where ATE denotes the average effect of fear in the population (i.e. fearful individuals tend to evacuate more) while d is the peer slope coefficient (whose estimate is positive as described above) and m is a positive constant whose exact value depends on the distributional assumptions chosen by the researcher. The implication for policy making purposes is that increasing awareness about danger from a hurricane using various channels can have a substantial effect. This is because the effect of a first wave of evacuations driven solely by fear i.e ATE will be diffused via the peer effect i.e., the $m \times d$ channel. Thus when the policy maker increases awareness of hurricanes risk, Mr. Jones evacuates due to fear and Mrs. Smith who is not scared will follow Mr. Jones because both share similar socio-economic profile. Thus peer effects can amplify the impact of information provided by policy makers.

4. Future Work

We believe that this research forms the starting point of a research agenda – one that aims to integrate both the perspectives of economists and non-economists. Our theoretical model suggests that naïve agents may not evacuate (on-time) and their decision depends also on their costs and benefits. These conclusions have not yet been tested in the field. The biggest obstacle here has been the lack of data. Given the fact that behavioral economics has been successful in explaining many other phenomena this hypothesis certainly needs to be tested, making it important to collect field data on this topic. The empirical model is lacking a lot of additional information that could improve estimates. Moreover, in the current analysis peers have been identified using similarity in attributes. In future work we would like to relax this assumption and determine peers based on locations. This would allow us to judge the relative importance of local and non-local information.

The more important task for the future of course would be to incorporate both hyperbolic discounting and peer effects into one model. The outcome of such a model needs to be thoroughly examined since peers may also affect the hyperbolic discount rate. There is some anecdotal evidence which suggest that peers play a role in activities like smoking, studying and weight loss. This requires both the development of theory as well as empirical modeling and testing. Moreover there is no data that will allow us to test a model that incorporates both features. In other words it is necessary to design new surveys and carry out new field studies to test these hypotheses. The last step in this research would be to create inter-disciplinary research involving both economists and non-economists. This will bring to the table both economic and non-economic factors driving the evacuation decision to provide an accurate understanding of this complex phenomenon. Finally, we intend to pursue this research further in the future and seek additional funding. This is a topical issue and we intend to apply to organizations like the NSF and DHS for furthering this research.

5. Technical Appendix

1. Empirical Model

$$Y=1 \text{ if } sx'b1+(1-s)x'b0+d(1-s)M+s\ error1+(1-s)\ error,$$
$$Med\ (error/\ x,s=0)=0$$

Where,
Y=1 if individual evacuates during Floyd
error1, error are unobservables
s=1 if fear of potential hurricanes is reported before hurricane season
x contains the socioeconomic attributes
M=P[s=1/z] is the peer variable where z=F(x) for some given F which maps the attributes into discrete social identifiers.

2. Construction of peer variable M

We use z=(C,A,R,W) where
C=j if lives in jth county for j=1…3 (there are 3 counties in the NC costal region)
A= sum_j=1…3 j a_j , where a_j=1 if individual falls in jth age bracket (we use 3: for young, middle aged and senior)
R=1 if white and 0 otherwise.
W= sum_j=1…3 j w_j, where w_j=1 if individual falls in jth income bracket (we use 3: for poor, middle class and upper class)

3. Variables and Descriptive statistics

Variables
Order =1 id mandatory order received
Pets =1 if owns a pet
Pasthurricane =1 if experience an hurricane before
Owns=1 if individual owns the house
Distance water= number of miles away the house is from the sea
Mobile=1 if lives in mobile home
Age= age in years
Married =1 if married
White =1 if white
Female=1 if female
Years= number of years spent in current county
Riskflood=1 if house is vulnerable to flood
Riskwind=1 if if house is vulnerable to wind
County2= if lives if the second county
County3 =if lives in the third county
M=P[s=1/z]

Descriptive statistics

Sample size=384 observations

Variable	Sample mean	Sample Std deviation
y	0.37	0.48
order	0.19	0.39
owns	0.84	0.36
mobile	0.21	0.41
age	49.96	17.56
married	0.66	0.47
white	0.84	0.36
female	0.61	0.48
Education level (1,2,3,4,5 with 1 lowest)	3.33	1.51
Distance water	9.26	10.57
Years	10.54	11.33
Risk flood	0.13	0.34
Riskwind	0.31	0.46
s	0.20	0.40

4. Estimation Results

Sample size=384 observations.

Variable	coefficient	t-statistic
Order	13.73	25.44
Pets	1.87	14.81
Pasthurricane	0.06	5.48
owns	-2.18	-15.80
mobile	0.53	3.35
age	-0.10	-30.85
Married	1.47	11.58
White	4.24	19.05
Female	2.70	53.21
years	-0.10	-13.65
Riskflood	3.79	19.41
Riskwind	2.36	13.34
County2	0.39	6.67
County3	-1.51	-23.53
M	9.03	32.67

* *the t-statistics has, asymptotically, the distribution of the standard normal variable. Thus, at conventional significance levels those variables are statistically significant.
** These above coefficients estimate those of the original model divided by that of education.
** The estimation is carried out in R. Model 2 yields qualitatively similar results and hence the table is omitted.

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