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TO VACCINATE OR TO PROCRASTINATE? THAT IS THE PREVENTION QUESTION

Robert Nuscheler, Kerstin Roeder

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Canadian Centre for Health Economics
Centre canadien en économie de la santé
155 College Street
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Abstract

Invoking Yaari's dual theory we develop a model of individual vaccination decisions that incorporates quasi-hyperbolic discounting (present-biasedness), risk aversion, and information. We test the resulting hypotheses for the flu season 2010/2011 using a representative German data set. It turns out that quasi-hyperbolic discounting men vaccinate with a significantly lower probability than exponential discounters; they tend to procrastinate. There is no such delay in the prevention behavior of women who tend to vaccinate despite their distorted time preference. Risk aversion is positively related to the probability to vaccinate for men, while the association is negative for women. Well informed individuals have a much higher propensity to vaccinate than poorly informed individuals. Our results suggest that public health policy should not only concentrate on providing information about the flu and the flu shot but also increase the awareness that distorted time preferences may have a bearing on individual prevention decisions.

JEL Classification: D03; D81; H42; I11; I18

Key words: flu shot, prevention, quasi-hyperbolic discounting, risk aversion, information, public health

Corresponding Author:

Robert Nuscheler
University of Augsburg
Department of Economics
Universitätsstr. 16
86159 Augsburg
Germany
Email: robert.nuscheler@wiwi.uni-augsburg.de
Phone: +49-821-598-4202
Fax: +49-821-598- 4232

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In delay there lies no plenty.
(William Shakespeare)

1 Introduction

Seasonal influenza is an infectious disease that may have serious consequences for those infected. The World Health Organization (2003a) estimates that worldwide annual influenza morbidity ranges from 5 to 15 per cent of the population and annual influenza mortality from 250,000 to 500,000.[1] As was demonstrated by the Spanish Flu almost 100 years ago (1919 to 1920), the Asian flu (1957), and the Hong Kong Flu (1968) death rates can be markedly higher. Viboud *et al.* (2006) estimate the number of deaths from these three pandemics to be 20 to 50 million for the Spanish Flu and around 1 million for each of the other two.

In the light of the substantial morbidity and mortality, pandemic preparedness is an important public health issue. Prevention is part of this preparedness including vaccination against influenza. The flu shot became available in the 1940s and the vaccine is generally deemed effective (see, *e.g.*, CDC 2014).[2] To lower the disease burden vaccination take up is crucial, especially for risk groups like the elderly. This is reflected in the World Health Organization's immunization target of 75 per cent in the age group 60 years and older (WHO 2003b). Based on this target the German immunization rates of about 60 per cent are too low.

Standard economic arguments, indeed, suggest that immunization rates will generally be too low. Vaccinated individuals can no longer infect others and incomplete internalization of this positive externality leads to insufficient immunization. Brito *et al.* (1991) were the first to analyze this problem from an economic perspective. They argue that, despite this externality, full immunization of the population is inefficient due to side-effects. But still, their *laissez-faire* outcome yields too low immunization rates. Geoffard and Philipson (1997) offer an additional argument for why full immunization will not obtain as a *laissez-faire* outcome: the prevalence elasticity. Vaccination lowers the risk of infection for those who remain susceptible thereby reducing their benefits of vaccination and with it the willingness to vaccinate.

To correct these market failures a better understanding of the determinants of individual vaccination decisions is needed. This was already pointed out by Mullahy (1999) who analyzed the determinants for obtaining a flu shot taking a demand side perspective. He investigates which individual characteristics are important for vaccination take-up and the role of the prevalence elasticity therein. Schmitz and Wübker (2011) argue that the supply side matters, that is, the

[1]For the case of Germany, the Robert Koch Institute (2013) reports that in the past ten years between 1 and 7 million additional doctor visits per year can be attributed to influenza (p. 35). Excess mortality ranges from 0 to 18,000 (p. 39).

[2]Due to the genetic drift of the influenza virus the vaccine needs to be adapted and annual vaccination is recommended.

quality of physicians. Maurer (2009) combines the demand and supply side to arrive at a more complete picture. Although all these papers advanced our understanding about the market for vaccination substantially, none of them dealt with the intertemporal nature of the immunization problem.

We argue that the decision to vaccinate is like an investment decision: the individual is confronted with expected costs today and expected benefits in the future so that discounting plays an important role. Research on human behavior indicates that discount functions are rather hyperbolic than exponential (see Frederick *et al.* (2002) for an overview), implying a lower discount factor over short horizons than over long horizons. In our theoretical framework we incorporate the resulting present-biasedness by adopting Laibson's (1997) quasi-hyperbolic discounting model and, to capture uncertainty, we combine Laibson's model with Yaari's (1987) dual theory. Our theory predicts that future orientation as measured by high discount factors is positively associated with the demand for vaccination. Present-biased individuals systematically over-estimate the present (the expected side-effects of vaccination) as compared to the future (the expected benefit of vaccination, namely, immunity). This present bias may lead to preference reversals, *i.e.*, to time-inconsistent preferences: an individual may plan to obtain a flu shot but once immunization is due not execute the plan and remain susceptible. Like O'Donoghue and Rabin (1999a, 1999b) we distinguish between naïve and sophisticated individuals. While sophisticated individuals are aware of their time-inconsistent preferences, naïve individuals are not. This implies that a sophisticated individual may take measures so as to commit her future self to her current self's immunization plan. If the required commitment device is sufficiently inexpensive, vaccination behavior of present-biased individuals will be very similar to the behavior of exponential discounters. Naïve individuals are unaware of their inclination to change plans. They will never purchase a commitment device implying lower immunization rates for present-biased individuals than for exponential discounters. Our model also predicts that risk aversion has an ambiguous effect on the willingness to vaccinate. The reason being that vaccination is risky (side-effects may or may not obtain) as well as no vaccination (risk of catching the flu). Finally, we argue that the extent of individual information about the flu and the flu shot is positively associated with the propensity of vaccination.

Using a German data set (Gesundheitsmonitor 2011) we test the hypotheses derived from our theoretical model for the flu season 2010/2011 and find strong support for most of them. The vaccination behavior of present-biased men is as if they were naïve. By contrast, the demand for immunization of present-biased women is not statistically different from the demand of exponential discounters, that is, women act as if they were sophisticated. More generally, as far as women are concerned, time preferences are not systematically related to vaccination behavior. In contrast to our theory, we find that for men future orientation is negatively associated with the willingness to vaccinate. The impact of risk aversion is found to be significantly positive for men and significantly negative for women. Finally, it turns out that rather subjective measures of information are strongly associated with vaccination behavior. The better informed individuals are the higher their willingness to vaccinate. Perhaps somewhat surprising, the effect of objective information has no significant impact on vaccination behavior.

To the best of our knowledge this is the first vaccination article that considers individual heterogeneity in time preferences, time-inconsistency, risk attitudes, and information.[3] This gap in the literature is surprising.[4] As early as in 1997 Cairns and van der Pol demonstrated that distorted time preferences matter in health domains. There is a considerable body of literature that investigates how time preferences relate to smoking behavior. Gruber and Kőszegi (2001), for instance, showed that time-inconsistent preferences help in explaining smoking behavior. More recent papers, *e.g.*, Harrison *et al.* (2010), Kang and Ikeda (2013), and Khwaja *et al.* (2007), confirm this finding.[5] Our paper contributes to this literature by considering prevention against the flu rather than prevention against smoking related diseases like lung cancer or heart attacks.

The remainder of the paper is organized as follows. The theoretical framework is presented in Section 2, followed by a description of the data set in Section 3. In Section 4 we present our findings and offer some concluding remarks in Section 5.

2 Theoretical framework

2.1 Setup

Consider a continuum of individuals and let their mass be normalized to one. There are three periods, namely, summer ($t = 0$), fall ($t = 1$), and winter ($t = 2$). Individuals know that they may contract the flu in period 2 unless they demand a flu shot in period 1. Suppose the individual goes without immunization, then the individual contracts the flu in period 2 with probability $\pi_L \in (0, 1)$. Catching the flu implies a loss of $L > 0$ monetary units. Think of these costs as lost income due to sickness absence from work, lost leisure time, or health care expenses.

By obtaining a flu shot in period 1 individuals can lower the probability of catching the flu in the winter. To simplify matters we assume that the flu shot offers perfect protection, that is, immunization rules out infection. While uncertainty is removed from period 2, demanding a flu shot introduces uncertainty in period 1. Although the flu shot is generally deemed safe, side effects may occur with some positive probability denoted $\pi_S \in (0, 1)$. In the event of side

[3]Parente *et al.* (2005) showed that information matters for vaccination take-up. The kind of information they consider, however, is not related to the vaccine or the process of vaccination but to knowledge about whether or not vaccination is being covered by their health plan. Unsurprisingly, individuals who know that vaccination is covered are more likely to obtain immunization than those who do not.

[4]In an earlier (entirely empirical) article tailored to public health professionals Nuscheler and Roeder (2012) use the same data set analyzed here. They do not investigate the role of time preferences and risk aversion on immunization decisions and only briefly discuss how information might impact vaccination behavior.

[5]Hyperbolic discounting may also be related to obesity (see Ikeda *et al.*, 2010).

effects, individuals face a loss $S > 0$ measured in monetary units.

In the fall, individuals have to decide whether or not to demand a flu shot. Here individuals have to choose between two lotteries. If the individual demands a flu shot, income in period 1 is uncertain while income in period 2 is safe. Should the individual go without immunization, then period 1 income is safe while period 2 income is uncertain. An additional complication is that individuals have to form expectations about the immunization rate in the population. Let $x \in [0, 1]$ denote the share of vaccinated individuals, then the probability of catching the flu conditional on being susceptible is $\pi_L(x)$, where $\pi'_L(x) < 0$. The negative derivative reflects the positive externality vaccination has on those who remain unprotected. Once individuals are vaccinated they can no longer contract the flu and, thus, no longer communicate the disease. This reduces the risk of catching the flu for those who refrained from obtaining the flu shot. To keep the analysis focussed we assume that all individuals form the same expectations and that expectations are confirmed in equilibrium. The resulting infection probability is denoted π_L.[6]

We model the choice between these risky alternatives by adopting Yaari's (1987) dual theory. In contrast to expected utility theory, where risk aversion is modeled considering a strictly increasing and strictly concave transformation of income levels but linear probabilities, Yaari's theory involves a distortion of probabilities but lets income levels enter linearly. We denote this distortion function $\phi : [0, 1] \to [0, 1]$ with $\phi(0) = 0$ and $\phi(1) = 1$. Risk aversion is expressed by overstating the probability of bad outcomes, that is, we have $\phi(\pi_L) > \pi_L$ and $\phi(\pi_S) > \pi_S$. Let $v_i = 1$ if individual i demands a flu shot and $v_i = 0$ otherwise. The utility of individual i in period t is then given by $U_{it}(v_i)$. With Y_{i2} denoting individual i's income level in period 2, second period utility can be written as

$$U_{i2}(1) = Y_{i2}, \tag{1}$$

$$U_{i2}(0) = Y_{i2} - \phi(\pi_L)L. \tag{2}$$

As individuals have to compare risky situations in an intertemporal context discounting of payoffs is crucial. Following Laibson (1997) we assume quasi-hyperbolic discounting also known as (β, δ)-preferences. The idea is that an individual's discount factor between two consecutive future periods is $\delta \in (0, 1]$ but between the current period and the subsequent period $\beta\delta$, with $\beta \in (0, 1]$. The parameter δ is the traditional discount factor whereas β is called the *present-bias* factor.[7] Figure 1 below illustrates discounting in our framework considering period 0 the current period.

[Figure 1 about here]

[6]In other other words, individuals take the probability π_L as given.

[7]This preference structure nests the standard (exponential) discounting model as a special case ($\beta = 1$).

2.2 Vaccination, time preferences, and risk aversion

In the fall (period 1), individuals have to compare the following two utility levels

$$U_{i1}(1) = Y_{i1} - \phi(\pi_S)S + \beta\delta Y_{i2}, \tag{3}$$

$$U_{i1}(0) = Y_{i1} + \beta\delta\left[Y_{i2} - \phi(\pi_L)L\right]. \tag{4}$$

Individual i demands a flu shot whenever $U_{i1}(1) > U_{i1}(0)$. This is the case if and only if

$$\beta\delta > \frac{\phi(\pi_S)S}{\phi(\pi_L)L}. \tag{5}$$

If the perceived expected loss from side effects is sufficiently small as compared to the perceived expected loss from staying unprotected, the individual demands a flu shot. This condition is more demanding the lower δ or β. This allows us to state our first two hypotheses.

Hypothesis 1 *Future oriented individuals (δ is high) have a higher inclination to demand vaccination than present oriented individuals (δ is low).*

Hypothesis 2 *Present-biased individuals ($\beta < 1$) have a lower inclination to demand vaccination than intertemporally unbiased individuals ($\beta = 1$).*

As mentioned above, risk aversion is incorporated into the analysis by distorting upwards the probability of adverse events. It seems natural to ask how an increase in risk aversion would affect the desirability of immunization. Both, the distorted probability in the numerator and in the denominator of equation (5) increase with risk aversion. Hence, we cannot generally say how the ratio of the two changes as a response to an increase in risk aversion.

Hypothesis 3 *The degree of risk aversion has an ambiguous directional effect on the demand for vaccination.*

2.3 Vaccination, time-inconsistency, and naïvety

An individual makes prevention plans for the fall already during summer time. From the perspective of period 0 the utility of vaccination and susceptibility are

$$U_{i0}(1) = Y_{i0} + \beta\delta\left[Y_{i1} - \phi(\pi_S)S\right] + \beta\delta^2 Y_{i2} \qquad \text{and} \tag{6}$$

$$U_{i0}(0) = Y_{i0} + \beta\delta Y_{i1} + \beta\delta^2\left[Y_{i2} - \phi(\pi_L)L\right], \tag{7}$$

respectively. Accordingly, from the perspective of period 0, vaccination in the fall is desirable if and only if $U_{i0}(1) > U_{i0}(0)$ which is equivalent to

$$\delta > \frac{\phi(\pi_S)S}{\phi(\pi_L)L}. \tag{8}$$

We find that an individual more likely *plans* to get vaccinated the higher the traditional discount factor δ. A comparison of equations (5) and (8) reveals that $\beta = 1$ (standard exponential discounting) yields time-consistent vaccination preferences: in the fall individuals stick to their summertime immunization plans. For $\beta \in (0, 1)$, however, the discount factor between periods 1 and 2 is $\beta\delta$ from the perspective of period 1 while it is δ from the perspective of period 0. As a result, preferences are time-inconsistent. Individuals that are unaware of their time-inconsistent preferences (naïve individuals), may plan to obtain immunization but eventually not execute the plan. By contrast, sophisticated individuals are aware of their inclination to change plans. These individuals would seek to commit their fall-self to the optimal plan of their summer-self. In case a commitment device is available and not too costly sophisticated individuals would purchase it.

Hypothesis 4 *Present-biased individuals that are aware of their time-inconsistent preferences (sophisticated individuals) have a higher inclination to obtain a flu shot than those who are unaware of their present bias (naïve individuals). If costless commitment is possible, vaccination behavior of sophisticated individuals would not differ from the behavior of exponential discounters.*

2.4 Vaccination and information

To incorporate risk aversion Yaari's dual theory puts a higher weight on the probability of adverse events, in our case the probability of side-effects and the probability of catching the flu. If an individual is afraid of side-effects the weight on the probability of side-effects may be higher than the one implied by risk aversion alone. Let $\widetilde{\phi}$ denote the probability distortion function that includes both, risk aversion and a general overstatement of side-effects occurring, then $\widetilde{\phi}(\pi_S) > \phi(\pi_S) > \pi_S$. We can write $\widetilde{\phi}(\pi_S) \equiv \alpha\phi(\pi_S)$, where $\alpha = \widetilde{\phi}(\pi_S)/\phi(\pi_S) > 1$. Equations (5) and (8) then become

$$\frac{\beta\delta}{\alpha} > \frac{\phi(\pi_S)S}{\phi(\pi_L)L} \quad \text{and} \quad \frac{\delta}{\alpha} > \frac{\phi(\pi_S)S}{\phi(\pi_L)L}, \tag{9}$$

respectively. Vaccination is, thus, less likely the higher α or the fear of side-effects. Whether or not α exceeds one likely depends on how well informed individuals are about the possibility of side-effects. As the flu shot is generally deemed safe, the fear of side effects likely identifies a poorly informed individual. This allows us to formulate our final hypothesis.[8]

Hypothesis 5 *As compared to poorly informed individuals, well informed individuals have a higher inclination to demand immunization.*

[8] Alternative ways to incorporate poor information is to consider an under-statement of the loss from infection or an over-statement of the loss from side-effects. As is clear from equation (9) this would not change Hypothesis 5.

3 Data and descriptive statistics

Our data is part of the Gesundheitsmonitor 2011 project, an annual survey on health, health care, and health behaviors financed by the Bertelsmann Stiftung and BarmerGEK (a large German public health insurer). The questionnaire study, conducted by the GfK Nuremberg (a market research institution), is representative for the German population and comprises 1,778 randomly selected individuals. Interviewers were in the field in spring 2011.[9] We were allowed to ask a great many of questions relating to the flu and the flu shot. After eliminating outliers and observations with missing values we arrive at an analysis sample with 660 observations. At the end of this section we provide more information regarding sample selection.

3.1 Dependent variable

Our dependent variable FLUSHOT is an indicator that assumes the value one whenever an individual reported to have obtained a flu shot for the 2010/2011 season and zero otherwise.[10] Table 3 below reveals that about 35 per cent of respondents in our analysis sample demanded immunization. With 32 per cent women generally have a lower inclination to demand a flu shot.

[Table 3 about here]

3.2 Time preferences

In order to facilitate testing of Hypotheses 1 and 2 we asked the following two questions to elicit individual time-preferences:[11]

(i) "Suppose you can choose between receiving 500 Euros today or some other amount in 1 year from now. What is the smallest amount you must be given in 1 year for which you would prefer to wait 1 year rather than receiving 500 Euros today?"

(ii) "Suppose you can choose between receiving 500 Euros in 10 years or some other amount in 11 years from now. What is the smallest amount you must be given in 11 years for which you would prefer to wait 11 years rather than receiving 500 Euros in 10 years?"

For each of the two questions individuals were asked to state their amount by selecting one of the following categories: 500-550, 551-600, 601-650, 651-700, 701-750, or to state some other

[9] More information on the Gesundheitsmonitor (Health Monitor) can be found on http://www.bertelsmann-stiftung.de.

[10] The explanation of variables and summary statistics can be found in the Appendix (see Tables 1 and 2, respectively.)

[11] In answering theses questions, individuals were asked to assume that there is no inflation during the time periods considered and that they will be alive with certainty at the end of the specified periods.

amount. If one of the first five categories was selected, we set the amount to the middle of the interval. For the last category we took the number that was entered in the questionnaire.

Adopting Laibson's (1997) quasi-hyperbolic discounting model (see Figure 1), we can infer the discount factor δ from the response to question (ii): $\delta = 500/(\text{amount requested in 11 years})$. Based on δ we define the indicator DELTAHIGH that assumes the value one if δ is strictly above its median, that is, when individuals are more future oriented than the median. This is the case for 32 per cent of respondents. Table 3 shows that men are more future oriented than women (41 versus 23 per cent). Our theory predicts a positive association between future orientation and the inclination to demand immunization. This is not reflected in our descriptive results. Overall future oriented individuals have a vaccination rate of 33 per cent while less future oriented ones have a vaccination rate of 36 per cent. Stratification by gender reveals that this surprising result is rooted in the vaccination behavior of men: the immunization rate of future oriented men amounts to 31 per cent while the one for less future oriented ones is 43 per cent. By contrast, women behave according to the theory. To account for this difference the econometric model allows for gender specific effects of discounting on vaccination behavior, that is, for discounting-gender interactions.[12]

Exponential discounters would respond identically to questions (i) and (ii), their preferences are time-consistent. Present-biased individuals have a lower discount factor between the present and the subsequent period than between two consecutive future periods. This implies that present-biased individuals would request a higher amount in question (i) than in question (ii). The responses allow us to calculate the present bias, $\beta = (\text{amount requested in 11 years})/(\text{amount requested in 1 year})$, and the discount factor between the present and the subsequent period, $\beta\delta = 500/(\text{amount requested in 1 year})$. Based on β we define the indicator variable HYPERBOLIC that assumes the value one whenever an individual is biased towards the present, that is, whenever $\beta < 1$. Overall we find 22 per cent hyperbolic discounters in our sample and 53 per cent exponential discounters. Present biasedness is more prevalent in males (24 per cent) than in females (20 per cent). The graph below provides an overview of the amounts requested in 1 and 11 years, respectively. Exponential discounters can be found on the diagonal, present biased individuals below the diagonal and those biased towards the future above it.

[Figure 2 about here]

Interestingly, hyperbolic discounters have a 7.4 percentage points smaller vaccination rate than those without a present bias. This effect is larger in males than in females (8.7 versus 6.5 percentage points) suggesting again that gender interactions should be considered in the econometric model.

[12] Ikeda *et al.* (2010) and Kang and Ikeda (2013) also found that the effect of discounting differs across gender.

3.3 Risk aversion

To elicit the degree of risk aversion respondents were presented the following two alternatives:

(i) "Consider a lottery, where you have a 50 per cent chance of winning 50 Euros. With the remaining 50 per cent chance you win 200 Euros."

(ii) "You receive some amount with certainty."

Individuals were then asked to name the smallest amount they must be given so as to choose alternative (ii). We presented them the following categories: 90-100, 101-110, 111-120, 121-130, 131-140, 141-150, or to state some other amount. If one of the first six categories was selected, we set the amount to the middle of the interval. For the last category we took the number that was entered in the questionnaire. For presentation purposes we divided all amounts by 100 to arrive at the variable RISKATTITUDE. We also defined the indicator variable RISKAVERSION that assumes the value 1 whenever the amount demanded in alternative (ii) is below the expected earnings of alternative (i), that is, whenever the amount is below 125 Euros. 57 per cent of individuals are considered risk averse. Risk aversion is more prevalent in females (59 per cent) than in males (56 per cent). Table 3 shows only a marginal difference in vaccination rates between risk averters and risk neutral or risk loving individuals. Again, stratification by gender provides more clear-cut results: there is a negative association between risk aversion and vaccination in females (minus 8 percentage points) while there is a positive association in males (plus 8 percentage points) calling for gender interactions.

3.4 Information

We construct three variables capturing different dimensions of information. First, the indicator variable SIDEEFFECTS assumes the value one if an individual is afraid of side-effects a flu shot might have. As the flu shot is generally considered safe the fear of side-effects likely identifies poorly informed individuals in the sense that side-effects are overstated. Second, the variable OBJINFO captures more objective information. Individuals were asked whether vaccination may *cause* influenza. At the time of the interview all marketed influenza vaccines in Germany comprised dead viruses ruling out infection through vaccination. Whenever individuals were aware of this impossibility, the variable OBJINFO was assigned the value one and the value zero if the response was 'yes' or 'I don't know.' Finally, individuals were asked to rate their state of information concerning the flu and the flu shot on a five-point scale. We defined the variable SUBJINFO and set it to one if the individual rated his or her information as good or very good and zero in all other cases.

Table 3 reveals strong associations between information measures and vaccination decisions. In case individuals are afraid of side-effects (19 per cent of the sample) their vaccination rate is about 29 percentage points smaller than otherwise. This effect is more pronounced for males (minus 32 percentage points) than for females (minus 25 percentage points). 28 per cent of individuals are objectively well informed about the decision problem at hand or, more dramatically, 72 per cent are objectively poorly informed. Objectively well informed individuals' propensity to vaccinate is around 20 percentage points higher than for poorly informed individuals. This effect is much stronger for females (24 percentage points) than for males (16 percentage points). Individuals that feel well informed (50 per cent of individuals in our sample) have a much higher inclination to demand a flu shot than poorly informed individuals (16 per cent). There are no marked differences across gender.[13]

3.5 Control variables

While most control variables are fairly self-explanatory some measures deserve a closer look. First, we control for health care access using the dummy variables PRIVATE and FAMILYDOC. The former variable is one if the respondent is enrolled in the private health insurance system which implies improved access to health care. The latter variable indicates whether or not the respondent has a family doctor – the practice where flu shots are usually administered. Second, the variable COMPLIANCE captures that a family doctor is a source of information. It assumes the value one whenever the respondent usually follows the vaccination recommendation of the family doctor. Third, the variable EGO measures the extent to which the positive externality is internalized, more precisely, the variable assumes the value one if the vaccination decision rests on the individual benefit alone and not on the social benefit of vaccination.[14] Household size, HHSIZE, and wether there are children below the age of 18 years in the household, CHILD18, may affect the individual benefit - social benefit tradeoff. The indicators CITY100 and CITY500 capture different degrees of urbanization that might have an impact on the risk of infection.

3.6 Sample selection

In Table 4 we provide information on how sample averages of key variables change upon sample selection. The full sample comprises 1,778 observations. In a first step we exclude individuals

[13]It should be noted that the correlation between our information variables is surprisingly low. It is -0.17 between SIDEEFFECTS and OBJINFO, -0.15 between SIDEEFFECTS and SUBJINFO, and 0.24 between SUBJINFO and OBJINFO (all p-values < 0.001).

[14]To measure whether individuals consider the positive externality of vaccination on others we exposed respondents to the following situation: "Consider a vaccine that perfectly protects you against contracting a disease. Vaccination has two effects. A: You cannot contract the disease and B: You cannot communicate the disease (infect others). How would you rate the relative importance of these two effects on a scale ranging from 1 (only A is important) to 7 (only B is important)?" 81 per cent respond that A and B are equally important (category 4 on the scale). Except for category 3 that was chosen by 7 per cent, the remaining categories range from around 2 per cent to 3 per cent. In the regression we consider the indicator variable EGO that takes the value one if the respondent responded that only effect A matters. In all other cases the externality is (partially) internalized.

below the age of 25 years as those usually do not consider the decision problem we want to analyze. Moreover, we drop all individuals with missing information on the flu shot (3 observations). As a result average age increases from 45.2 to 49.5 years and the share of individuals reporting to be at least in good health falls from 30 to 26 per cent. The remaining variables remain stable. In a second step we eliminate all individuals with missing information on time preferences. The large drop in sample size from 1,533 to 902 suggests that a considerable fraction of respondents may have had problems comprehending the associated decision problems. As we can see from the table below these individuals were older than the sample average, had lower household income and were less healthy. In a third step we exclude all individuals with missing information on explanatory variables to arrive at a sample size of 697 observations. As compared to the full sample males are over-represented and household income is higher. There is a considerable drop in the average β suggesting an outlier problem.[15] Sample averages of the remaining variables do not systematically differ between the full and the selected sample.

[Table 4 about here]

There are a number of individuals in the sample that request very large amounts in 1 year or in 11 years in exchange for 500 Euros today or in 10 years, respectively. In a final step we exclude all individuals that requested more than 2000 Euros in 1 year or in 11 years. In addition we drop all individuals with values below 500 Euros (2 observations). This implies that we concentrate on individuals with discount rates between 0 and 300 per cent.[16] We arrive at an analysis sample size of 660 observations. In a robustness analysis we investigate how sample selection on time preferences affects regression results.

4 Results

4.1 Empirical model

Our explanatory variable FLUSHOT is binary so that discrete choice models are in order. The theory suggests that the probability to obtain a flu shot depends on time preferences, risk attitudes, and the extent to which an individual is informed about the decision problem at hand. This gives rise to the following probability model

$$P(FLU = 1) = F(\text{time preferences, risk aversion, information, controls}). \qquad (10)$$

The descriptive analysis revealed some marked differences across gender in the effects of our variables of interest on immunization decisions. Consequently, we consider interaction terms of

[15]One individual requested 625 Euros in 1 year and 500,000 Euros in 11 years implying $\beta = 800$ but has at least one missing in the remaining variables.

[16]This is exactly the same range of discount rates following from the questionnaire used by Ikeda *et al.* (2010) and Kang and Ikeda (2013).

gender with time preferences, risk aversion, and information measures. As the coefficients on interaction terms in discrete choice models like the Logit or Probit only measure the interaction over and above the interaction implied by the non-linearity of the model (see, *e.g.*, Greene 2010) we consider a linear probability model. This model is inherently heteroscedastic calling for robust estimation of the covariance matrix.[17] In the following we report HC3 standard errors as they tend to involve the smallest bias when errors are indeed heteroscedastic (see, *e.g.*, Angrist and Pischke, 2009, pp. 293-308.)

4.2 Model specification

Regression results are shown in Table 5 below. The smallest model one can possibly think of in our context is presented in the first column (Model 1). From our theoretical framework we know that the discount factor, δ, affects the propensity to vaccinate. For exponential discounters this is the only relevant influence of time preferences on immunization behavior. This also applies to quasi-hyperbolic discounters that are aware of their time-inconsistent preferences. By contrast, actual vaccination behavior of naïve quasi-hyperbolic discounters is determined by the discount factor between the present and the subsequent period, $\beta\delta$. Although we are unable to distinguish between naïve and sophisticated individuals the coefficients reveal that the probability to vaccinate significantly increases with $\beta\delta$ for men but not for women. In other words, quasi-hyperbolically discounting men behave as if they were naïve while quasi-hyperbolically discounting women behave as if they were sophisticated (see Hypothesis 4). These results are qualitatively robust across specifications.

Our descriptive analysis delivered a puzzling result for men: the propensity to vaccinate was found to be negatively associated with the discount factor δ (see Table 3). This result still holds when considering a regression analysis. The effect of the discount factor is significantly negative for men and not statistically different from zero for women. Inspection of the richer regression models 2 through 5 shows that this conundrum remains when taking individual heterogeneity into account. There is, thus, no support for Hypothesis 1 but strong support for Hypothesis 2.

The theory offered no guidance about how risk attitudes relate to individual vaccination decisions (see Hypothesis 3) so that teasing out the directional effect of risk preferences on immunization decisions is largely an empirical exercise. In Model 2 we add risk attitudes of respondents and find that a higher certainty equivalent, that is, lower risk aversion implies a lower probability to vaccinate for men. A 100 Euro increase in the certainty equivalent reduces the probability to demand a flu shot by 9 percentage points. For females the effect is similarly large in absolute terms but points in the opposite direction. While both effects are fairly robust across specifications the effect for women reaches statistical significance only in the full model.

[17] Apart from the first model presented in Table 5 below the Breusch-Pagan test rejects homoscedasticity at conventional significance levels.

Finally, note that the coefficients measuring the impact of time preferences are robust to adding individual risk attitudes.

Our final conjecture, Hypothesis 5, states that poor information about the decision problem at hand is negatively associated with the willingness to vaccinate. In Model 3 we add three measures capturing individual information, the fear from side-effects and an objective as well a subjective information measure. Apart from our objective information measure we find firm support for Hypothesis 5. If an individual is afraid of the side-effects a flu shot might have, the probability to vaccinate is 24 and 17 percentage points lower for men and women, respectively. If an individual feels well informed about the flu and the flu shot the probability to vaccinate is 34 percentage points lower for both men and women. These results suggest that public health policy should concentrate on educating individuals that the vaccine is generally considered safe. Consistent and readily available information about the flu and the flu shot may increase the share of individuals that feel well informed which, in turn, may increase the demand for vaccination.

These policy recommendations rest on a causal interpretation of our regression results. One may argue, however, that the information measures are endogenous. An individual that got immunization and experienced no side-effects may claim that he or she is not afraid of side-effects. The coefficient estimate would then be biased away from zero due to simultaneous causality. This argument can be extended to the objective information measure: the act of obtaining a flu shot may generate information simply because nursing staff provides it through counseling individuals. As far as subjective information is concerned, it may be that vaccinated individuals only claim to be well informed so as to convey that they made an informed choice. This argument, however, also works in the opposite direction. Individuals that go without immunization may have the exact same incentive. They may, for instance, claim that they are afraid of side-effects to justify their susceptibility status. Whether objective information is indeed acquired in the process depends on how flu shots are being administered. Since the flu shot is a standard procedure detailed explanations about the costs and benefits of vaccination are unlikely. Also note that our objective information measure contains very specific information, namely, knowledge about the impossibility to contract the flu through the vaccine. Overall there seems to be no strong case for endogeneity of our information measures. After all there are only minor changes in coefficient estimates of our main variables of interest, namely, time preferences, suggesting a small endogeneity bias if any.

In Models 4 and 5 we add regional information and socio-economic as well as socio-demographic information, respectively. While residence at the regional state level only has little impact on regression results, coefficient estimates tend to get smaller in absolute terms when the full set of control variables is considered. To account for individual heterogeneity we adopt Model 5. Although this implies a considerable drop in the degrees of freedom the precision of the time preference coefficients improves.

4.3 Robustness analysis

We only selected individuals into our sample that requested amounts of 2000 Euros and below in years 1 and 11 in exchange for a payment of 500 Euros immediately or in 10 years, respectively. In Table 6 below we assess the robustness of our regression results to variations in sample selection criteria.

A comparison of Models 5 and 5a reveals that elimination of 12 individuals with annual interest rates between 200 and 300 per cent does not change our regression results. Due to the lower number of observations, point estimates are less precise. Relaxing selection criteria to also include individuals with interest rates between 300 and 500 per cent does not affect our results (Model 5b). There are larger changes in coefficient estimates when relaxing selection criteria even further (Model 5c). As these changes are rooted in the vaccination behavior of only four individuals there is a strong case for not selecting individuals with interest rates between 500 and 900 per cent into our analysis sample.

To measure the impact of time preferences on vaccination behavior we include the standard discount factor δ as a regressor as well as the potentially biased discount factor $\beta\delta$. By construction these two measures are correlated (30 per cent). Interacting these variables with gender aggravates this problem considerably. The gender specific correlations between these two variables are 90 per cent for men and 88 per cent for women.[18] To assess whether the validity of our regression results is undermined by imperfect multi-collinearity we stratify our sample with respect to gender. This reduces the correlation between the two time preference variables to 32 and 28 per cent for men and women, respectively. In Table 7 in the Appendix we present Models 4 and 5 for men and women.[19] As compared to the joint analysis there are only negligible changes in coefficient estimates. Due to the considerable drop in sample size, however, point estimates are less precise so that we prefer gender interactions over gender stratification.

Rather than sample stratification collinearity can be addressed by resorting to a variable other than $\beta\delta$ to capture the impact of biased time preferences, β being the natural candidate.[20] Model 6 in Table 6 shows that our results are qualitatively robust to this alternative specification. Note, however, that β cannot have an independent effect on the probability to vaccinate (see equation (5)) so that, strictly speaking, Model 6 is misspecified. At least the coefficients on time preference measures should be interpreted very cautiously.

[18] The gender specific correlations between our three information measures are very small. Only the correlation between objective and subjective information is around 40 per cent. The remaining correlations are well below 10 per cent.

[19] In Models 1 through 3 all variables are interacted with gender so that the regression results of the full sample are identical to the ones of the stratified samples.

[20] The correlation between δ and β is 2 per cent for men and 42 per cent for women.

5 Conclusion

We developed a theoretical model based on Yaari's (1987) dual theory to advance our understanding of the impact of time preferences on the willingness to vaccinate. We also included risk attitudes and misperceptions in terms of an over-estimation of the probability of side-effects and an under-estimation of the benefits of vaccination. Due to the random occurrence of both, side-effects and the flu, it is not clear per se how risk aversion would affect the propensity to obtain immunization. In contrast, the theory offered clear-cut predictions for time preferences. Future oriented individuals are expected to have a higher propensity to vaccinate than less future oriented ones. Invoking Laibson's (1997) quasi-hyperbolic discounting model we find that present-biased individuals have time-inconsistent vaccination preferences in the sense that preference reversals may obtain. More precisely, quasi-hyperbolic discounters may plan to demand immunization but eventually change their plan once vaccination is due. Other than naïve individuals, sophisticated individuals are aware of their inclination to change plans. In case a sufficiently inexpensive commitment device is available, sophisticated individuals can overcome this time-inconsistency.

Using a German data set (Gesundheitsmonitor 2011) we found that the vaccination behavior of quasi-hyperbolically discounting men is as if they were naïve. By contrast, quasi-hyperbolically discounting women decide as if they were sophisticated. To shed light on the mechanism behind these results, future research should focus on how women bind their future selves to current vaccination plans. Is there any commitment device involved or do women simply act 'resolute', *i.e.*, refrain from changing plans (Hey and Lotito, 2009)? Another question for future research is to address the puzzle that for men future orientation is negatively associated with the demand for immunization. For women time preferences generally have no explanatory power. These results show that time preferences are key to understand the insufficient immunization rates. Too low immunization rates not only obtain because individuals fail to internalize the positive externality of immunization but also because of the inter-temporal nature of the problem.

We included a number of covariates into the analysis that could otherwise cause omitted variable bias. Most importantly, we controlled for individual risk attitudes. We found that risk aversion is positively (negatively) associated with the willingness to vaccinate for men (women). Except for objective information, we found very strong associations between the degree of information and the probability of obtaining immunization. If individuals are afraid of side effects – which, for the most part, would be for no good reason – the willingness to vaccinate is dramatically lower (16 percentage points on average). If individuals feel good informed about the pros and cons of vaccination, then immunization rates go up by 27 percentage points. Wether or not individuals are objectively well informed appears to be irrelevant.

A standard policy measure to mitigate time-inconsistent vaccination decisions are subsidies.

This 'bonus' should be paid upon vaccination, any delay would be more costly due to the present-bias. The efficacy crucially depends on targeting. Given our results such a bonus should be targeted to men. Note that this bonus should be paid on top of the subsidy that aims at correcting the incomplete internalization of the vaccination externality. This is similar to Gruber and Kőszegi (2001) who argue that, due to the 'internality', the optimal cigarette tax should be higher than the one that only corrects for the externality of smoking. To help hyperbolic discounters to overcome their commitment problem, a commitment device is needed. Scheduling an appointment with the family doctor for the fall or already ordering the vaccine in the summer serve as examples. As individuals are generally free to do so the missing awareness of present-biasedness appears to be the main problem. Public health policy should, thus, not only provide readily available and concise information about the flu and the flu shot but also emphasize that individual prevention behavior may be hampered by procrastination.

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Table 1: Explanation of variables.

Dependent variable	
FLUSHOT	= 1 if the individual reported to have obtained a flu shot for the 2010/2011 season, 0 else
Time preferences	
δ	= 500 / Amount requested in 11 years
β	= Amount requested in 11 years / Amount requested in 1 year
$\beta\delta$	= 500 / Amount requested in 1 year
HIGHDELTA	= 1 if δ is strictly above its median, 0 else
HYPERBOLIC	= 1 if $\beta < 1$, 0 else
Risk attitude	
RISKATTITUDE	= certainty equivalent to the lottery
RISKAVERSION	= 1 if the certainty equivalent is strictly below expected earnings (lower than 125 Euros), 0 else
Information measures	
SIDEEFFECTS	= 1 if afraid of side-effects from vaccination, 0 else
OBJINFO	= 1 if known that vaccination cannot cause infection, 0 else
SUBJINFO	= 1 if feels good or very good informed about the flu and the flu shot, 0 else
Control variables	
FEMALE	= 1 if female, 0 else
AGE	nine age categories ranging from 25-29 years to 65-69 years[1]
INCOME	nine categories for household income ranging from 0 to 5000+ Euros[2]
EDUCATION	seven categories for educational achievement (degrees)
HHSIZE	four indicators for household size (1, 2, 3, and 4+ persons)[3]
REGIONALSTATE	seventeen dummy variables indicating residence in regional state[4]
EAST	= 1 if residence in former East-Germany, 0 else
CHILD18	= 1 if children under the age of 18 years live in the same household, 0 else
GERMAN	= 1 if of German nationality, 0 else
MARRIED	= 1 if married, 0 else
CITY100	= 1 if residence in a city with 100,000 to 499,999 inhabitants, 0 else
CITY500	= 1 if residence in a city with at least 500,000 inhabitants, 0 else
FULLTIME	= 1 if employed full-time, 0 else
SELFEMP	= 1 if self-employed, 0 else
CIVIL	= 1 if civil servant, 0 else
PENSIONER	= 1 if pensioner, 0 else
STUDENT	= 1 if student, 0 else
WHITECOLLAR	= 1 if white collar worker, 0 else
BLUECOLLAR	= 1 if blue collar worker, 0 else
HCWORKER	= 1 if health care worker, 0 else
EGO	= 1 if reported to completely ignore the positive vaccination externality, 0 else
FAMILYDOC	= 1 if the individual has a family doctor, 0 else
COMPLIANCE	= 1 if the individual follows the vaccination recommendation of the family doctor, 0 else
PRIVATE	= 1 if insured in the private health insurance system, 0 else
HEALTH	= 1 if self-rated health is good or very good, 0 else

Notes: [1]For the descriptive statistics the variable AGE was assigned the middle of the age bracket, that is, 27 years for the first and 67 years for the last age category, respectively. [2]Income brackets (in Euros): 0-499; 500-999; 1,000-1,499; 1,500-1,999; 2,000-2,499; 2,500-2,999; 3,000-3,999; 4,000-4,999; 5,000+. For the descriptive statistics the variable INCOME was assigned the middle of the income bracket except for the highest bracket where we set household income equal to 5,000. [3]For the descriptive statistics the variable HHSIZE is assigned the value of the respective category. [4]There are 17 indicators for 16 regional states as we distinguish between East-Berlin and West-Berlin.

Table 2: Summary statistics.

Variable	N	Mean	Std. Dev.	Min	Max
Dependent variable					
FLUSHOT	660	0.352	0.478	0	1
Time preferences					
δ	660	0.752	0.140	0.250	0.952
β	660	1.013	0.191	0.288	2.069
$\beta\delta$	660	0.750	0.145	0.250	0.952
HIGHDELTA	660	0.321	0.467	0	1
HYPERBOLIC	660	0.217	0.412	0	1
Risk attitude					
RISKATTITUDE	660	1.242	0.459	0.250	5
RISKAVERSION	660	0.571	0.495	0	1
Information measures					
SIDEEFFECTS	660	0.189	0.392	0	1
OBJINFO	660	0.277	0.448	0	1
SUBJINFO	660	0.497	0.500	0	1
Control variables					
FEMALE	660	0.485	0.500	0	1
AGE	660	45.212	11.987	27	67
INCOME	660	2,627.652	1,154.136	250	5000
HHSIZE	660	1.715	0.641	1	4
CHILD18	660	0.298	0.458	0	1
GERMAN	660	0.995	0.067	0	1
MARRIED	660	0.673	0.470	0	1
CITY100	660	0.150	0.357	0	1
CITY500	660	0.152	0.259	0	1
FULLTIME	660	0.464	0.499	0	1
SELFEMP	660	0.038	0.191	0	1
CIVIL	660	0.079	0.270	0	1
PENSIONER	660	0.288	0.453	0	1
STUDENT	660	0.003	0.055	0	1
WHITECOLLAR	660	0.441	0.497	0	1
BLUECOLLAR	660	0.097	0.296	0	1
HCWORKER	660	0.159	0.366	0	1
EGO	660	0.017	0.128	0	1
FAMILYDOC	660	0.927	0.260	0	1
COMPLIANCE	660	0.633	0.482	0	1
PRIVATE	660	0.059	0.236	0	1
HEALTH	660	0.326	0.469	0	1

Table 3: Immunization rates and the role of time preferences, risk aversion, and information.

			Future oriented		Hyperbolic discounter		Risk averter		Afraid of side-effects		Objective information		Subjective information	
		∅	yes	no	yes	no	yes	no	yes	no	yes	no	yes	no
FLU= 1	all	0.351	0.325	0.364	0.294	0.368	0.350	0.353	0.120	0.406	0.497	0.296	0.543	0.163
	women	0.322	0.361	0.307	0.270	0.335	0.287	0.371	0.121	0.374	0.500	0.261	0.531	0.149
	men	0.379	0.307	0.430	0.313	0.400	0.413	0.338	0.119	0.434	0.495	0.331	0.552	0.178
∅	all	1.000	0.321	0.679	0.217	0.783	0.571	0.429	0.189	0.811	0.277	0.723	0.497	0.503
	women	0.485	0.225	0.775	0.197	0.803	0.586	0.414	0.206	0.794	0.256	0.744	0.453	0.547
	men	0.515	0.412	0.588	0.235	0.765	0.556	0.444	0.174	0.826	0.297	0.703	0.538	0.462

Notes: Future oriented (HIGHDELTA = 1), Hyperbolic discounter (HYPERBOLIC = 1), Risk averter (RISKAVERSION = 1), Afraid of side-effects (SIDEEFFECTS = 1), Objective information (OBJINFO = 1), Subjective information (SUBJINFO = 1).

Table 4: Sample selection.

Sample	FLUSHOT	δ	β	FEMALE	AGE	INCOME	EAST	HEALTH
full sample	0.347	0.733	2.084	0.515	45.218	2,455.709	0.209	0.303
	(1,775)	(1,115)	(1,075)	(1,778)	(1,778)	(1,778)	(1,778)	(1,761)
age $\geq$ 25 years and FLUSHOT not missing	0.376	0.732	2.272	0.494	49.469	2,465.917	0.205	0.261
	(1,533)	(937)	(902)	(1,533)	(1,533)	(1,533)	(1,533)	(1,516)
δ and β not missing	0.345	0.733	2.272	0.459	47.094	2,584.812	0.202	0.325
	(902)	(902)	(902)	(902)	(902)	(902)	(902)	(893)
no missings in explanatory variables	0.351	0.736	1.467	0.486	45.115	2,620.029	0.202	0.325
	(697)	(697)	(697)	(697)	(697)	(697)	(697)	(697)
analysis sample	0.352	0.752	1.013	0.485	45.212	2,627.652	0.202	0.326
	(660)	(660)	(660)	(660)	(660)	(660)	(660)	(660)

Notes: Sample averages of key variables. Number of observations in parentheses.

Table 5: Flu Shot – Model Specification

Explanatory variable	Model 1	Model 2	Model 3	Model 4	Model 5
$\delta\times$MALE	-0.661*** (0.234)	-0.714*** (0.242)	-0.796*** (0.205)	-0.764*** (0.207)	-0.918*** (0.191)
$\delta\times$FEMALE	-0.110 (0.255)	-0.062 (0.254)	-0.070 (0.237)	-0.087 (0.240)	-0.004 (0.239)
$\beta\delta\times$MALE	0.584*** (0.207)	0.545*** (0.209)	0.433** (0.194)	0.373* (0.197)	0.385** (0.193)
$\beta\delta\times$FEMALE	0.220 (0.262)	0.258 (0.269)	0.146 (0.253)	0.127 (0.256)	0.077 (0.246)
RISKATTITUDE$\times$MALE		-0.090* (0.050)	-0.080** (0.037)	-0.086** (0.035)	-0.114** (0.049)
RISKATTITUDE$\times$FEMALE		0.089 (0.090)	0.105 (0.073)	0.099 (0.075)	0.097* (0.057)
SIDEEFFECTS$\times$MALE			-0.244*** (0.053)	-0.261*** (0.052)	-0.165*** (0.056)
SIDEEFFECTS$\times$FEMALE			-0.174*** (0.053)	-0.187*** (0.053)	-0.145*** (0.055)
OBJINFO$\times$MALE			0.071 (0.056)	0.073 (0.058)	0.045 (0.055)
OBJINFO$\times$FEMALE			0.091 (0.064)	0.094 (0.066)	0.117* (0.069)
SUBJINFO$\times$MALE			0.342*** (0.048)	0.327*** (0.050)	0.294*** (0.048)
SUBJINFO$\times$FEMALE			0.336*** (0.053)	0.328*** (0.054)	0.241*** (0.053)
FEMALE	-0.204 (0.235)	-0.561* (0.305)	-0.608** (0.259)	-0.614** (0.263)	-0.679*** (0.236)
R^2 (adjusted)	0.010	0.014	0.202	0.213	0.361
Breusch-Pagan test (p-value)	0.108	0.044	0.000	0.000	0.000
N	660	660	660	660	660
Degrees of freedom	654	652	646	630	587
Joint significance - Wald test p-values					
Time preferences	0.026	0.024	0.004	0.008	0.000
Risk aversion		0.125	0.035	0.021	0.016
Information			0.000	0.000	0.000
Regional state indicators				0.085	0.290
Remaining control variables					0.000

Notes: Robust hc3 standard errors in parentheses. Significance levels: *p<0.1, **p<0.05, ***p<0.01.

Table 6: Flu Shot – Robustness Analysis

Explanatory variable	Model 5	Model 5a	Model 5b	Model 5c	Model 6
Amount requested - upper bound	2000	1500	3000	5000	2000
δ×MALE	-0.918*** (0.191)	-0.839*** (0.199)	-0.889*** (0.174)	-0.715*** (0.232)	-0.514** (0.204)
δ×FEMALE	-0.004 (0.239)	-0.069 (0.249)	0.003 (0.208)	-0.091 (0.205)	0.056 (0.196)
$\beta\delta$×MALE	0.385** (0.193)	0.383* (0.210)	0.361* (0.187)	0.272 (0.203)	
$\beta\delta$×FEMALE	0.077 (0.246)	0.228 (0.277)	0.071 (0.218)	0.160 (0.214)	
β×MALE					0.269* (0.158)
β×FEMALE					0.010 (0.136)
RISKATTITUDE×MALE	-0.114** (0.049)	-0.149*** (0.034)	-0.124*** (0.041)	-0.116*** (0.042)	-0.122*** (0.043)
RISKATTITUDE×FEMALE	0.097* (0.057)	0.071 (0.059)	0.105** (0.048)	0.119** (0.049)	0.096* (0.057)
SIDEEFFECTS×MALE	-0.165*** (0.056)	-0.177*** (0.056)	-0.162*** (0.056)	-0.162*** (0.057)	-0.165*** (0.057)
SIDEEFFECTS×FEMALE	-0.145*** (0.055)	-0.137** (0.055)	-0.145*** (0.054)	-0.151*** (0.054)	-0.145*** (0.055)
OBJINFO×MALE	0.045 (0.055)	0.045 (0.055)	0.045 (0.055)	0.053 (0.055)	0.044 (0.055)
OBJINFO×FEMALE	0.117* (0.069)	0.120* (0.069)	0.117* (0.068)	0.126* (0.068)	0.116* (0.068)
SUBJINFO×MALE	0.294*** (0.048)	0.279*** (0.049)	0.295*** (0.048)	0.286*** (0.049)	0.292*** (0.048)
SUBJINFO×FEMALE	0.241*** (0.053)	0.242*** (0.054)	0.242*** (0.052)	0.237*** (0.052)	0.241*** (0.053)
FEMALE	-0.679*** (0.236)	-0.711*** (0.249)	-0.696*** (0.231)	-0.632** (0.249)	-0.397 (0.392)
R^2 (adjusted)	0.361	0.360	0.365	0.356	0.359
Breusch-Pagan test (p-value)	0.000	0.000	0.000	0.000	0.000
N	660	648	665	669	660
Degrees of freedom	587	575	592	596	587
Joint significance - Wald test p-values					
Time preferences	0.000	0.001	0.000	0.038	0.002
Risk aversion	0.016	0.000	0.001	0.002	0.011
Information	0.000	0.000	0.000	0.000	0.000

Notes: Robust hc3 standard errors in parentheses. Significance levels: *p<0.1, **p<0.05, ***p<0.01.

Table 7: Flu Shot – Stratification by gender

Explanatory variable	Model 4			Model 5		
Sample	ALL	MALE	FEMALE	ALL	MALE	FEMALE
$\delta\times$MALE	-0.764*** (0.207)	-0.810*** (0.220)		-0.918*** (0.191)	-0.947*** (0.230)	
$\delta\times$FEMALE	-0.087 (0.240)		-0.065 (0.249)	-0.004 (0.239)		-0.007 (0.261)
$\beta\delta\times$MALE	0.373* (0.197)	0.379* (0.203)		0.385** (0.193)	0.339 (0.228)	
$\beta\delta\times$FEMALE	0.127 (0.256)		0.095 (0.263)	0.077 (0.246)		0.035 (0.264)
RISKATTITUDE$\times$MALE	-0.086** (0.035)	-0.082** (0.037)		-0.114** (0.049)	-0.125** (0.055)	
RISKATTITUDE$\times$FEMALE	0.099 (0.075)		0.104 (0.077)	0.097* (0.057)		0.098* (0.058)
SIDEEFFECTS$\times$MALE	-0.261*** (0.052)	-0.257*** (0.054)		-0.165*** (0.056)	-0.165** (0.064)	
SIDEEFFECTS$\times$FEMALE	-0.187*** (0.053)		-0.192*** (0.054)	-0.145*** (0.055)		-0.158** (0.063)
OBJINFO$\times$MALE	0.073 (0.058)	0.077 (0.060)		0.045 (0.055)	0.056 (0.061)	
OBJINFO$\times$FEMALE	0.094 (0.066)		0.092 (0.067)	0.117* (0.069)		0.094 (0.079)
SUBJINFO$\times$MALE	0.327*** (0.050)	0.328*** (0.051)		0.294*** (0.048)	0.295*** (0.053)	
SUBJINFO$\times$FEMALE	0.328*** (0.054)		0.326*** (0.056)	0.241*** (0.053)		0.268*** (0.064)
FEMALE	-0.614** (0.263)			-0.679*** (0.236)		
R^2 (adjusted)	0.213	0.206	0.199	0.361	0.378	0.317
Breusch-Pagan test (p-value)	0.000	0.000	0.000	0.000	0.004	0.000
N	660	340	320	660	340	320
Degrees of freedom	630	317	297	587	276	254
Joint significance - Wald test p-values						
Time preferences	0.008	0.001	0.934	0.000	0.000	0.988
Risk aversion	0.021	0.028	0.177	0.016	0.023	0.092
Information	0.000	0.000	0.000	0.000	0.000	0.000

Notes: Robust hc3 standard errors in parentheses. Significance levels: *p<0.1, **p<0.05, ***p<0.01.

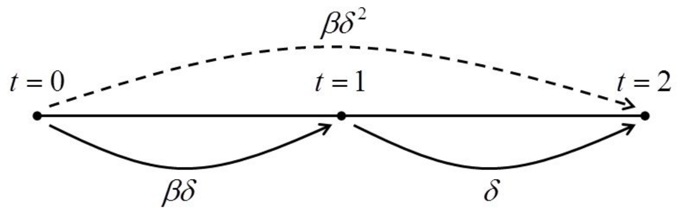

Figure 1: Quasi-hyperbolic discounting with three periods.

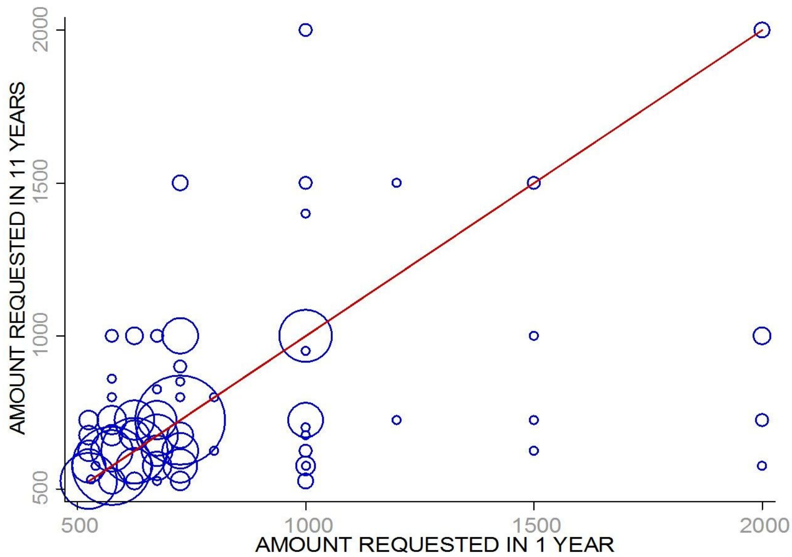

Figure 2: Time Preferences and Quasi-Hyperbolic Discounting. Observations on the 45-degree line indicate exponential discounting, observations below point to a bias towards the present while those above reveal a bias towards the future. Circle sizes are proportional to the respective frequencies.