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Household disability and time preferences: Evidence from incentivized experiments in Vietnam *

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Abstract

This paper investigates individual time preferences between individuals living in a disability household and those who live in a non-disability household in Vietnam. Using randomized primes together with experimental tasks to elicit time preferences, our empirical results show that individuals living in a disability household are (i) more likely to be present biased, and (ii) more patient. The effects are even more pronounced when the disability happened recently (within the last 8 years). These findings show causal evidence that time preferences differ among more vulnerable groups of society and may be one cause for their often observed adverse socioeconomic conditions.

Keywords: Disability, Time preferences, Priming, Vietnam

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1 Introduction

A large body of literature focuses on poverty and disability revealing that both are intimately linked (Banks et al. 2017; Groce et al. 2011; Palmer 2011). Independently of the poverty measure and the applied poverty line, many studies in developing countries find higher poverty rates for people with disabilities (PWD) compared to persons without disabilities in the same setting (Braithwaite and Mont 2009; Banks et al. 2021; Trani and Loeb 2012; Trani et al. 2015; Mitra et al. 2013). For example, Mont and Cuong (2011) estimate that the poverty rate in Vietnam was seven percentage points higher for PWDs compared to persons without disabilities.

Even households that include people with disabilities, with the same level of income as a household without people with disabilities are still likely to be effectively poorer (Braithwaite and Mont 2009). Quantifying their magnitude is challenging and findings vary considerably among studies (Mitra et al. 2017). The maybe most frequently found argument are the higher costs for people with disabilities or households with a disabled family member. For example, Braithwaite and Mont (2009) estimate that the extra cost of disability are nine percent of income in Vietnam. The costs are found to be highest for persons with severe disabilities, and among persons with disabilities living alone or in small sized households (Mitra et al. 2017). However, beyond the external constraints, also internal constraints such as certain behaviors can be one reason for these frequently observed adverse economic outcomes.

Every day, household members make decisions that include costs and benefits that occur at different points in time. Some of these decisions are likely to affect future economic outcomes of the entire household, e.g. whether parents invest resources in children's education. Thus, many choices in life of persons with and without disabilities require decisions involving trade-offs among costs and benefits that occur at different points in time, and studies found that individuals typically prefer to receive and consume a given reward rather sooner than later (Camerer and Loewenstein 2004). Existing studies show that these intertemporal choice decisions differ among subgroups. The probably most investigated determinant is age (Sozou and Seymour 2003; Read and Read 2004; Strulik and Trimborn 2018) as well as gender (Kirby and Maraković 1996; Pender 1996; Castillo et al. 2011; Dittrich and Leipold 2014; Meier and Sprenger 2010). The literature shows that different subgroups tend to rate the future differently than others, which might affect their economic decision making process.

Disability households form a vulnerable group whose socioeconomic outcomes are adversely affected and so far no knowledge exists on whether this subgroup might have different time preferences than households who do not live with a disabled person. Studies show that disability households are more likely to have lower levels of education and employment, poorer health outcomes, higher levels of malnourishment, and, partly as a result, they live disproportionately in poverty (United Nations 2018; Mont and Cuong 2011). Additionally, these households are often faced with increased costs of living caused by the need for additional health services and assistive devices (Mont and Cuong 2011; Cote 2021). Socioeconomic determinants of time preferences are income and poverty, education, health and risk aversion. Income is found to be inversely related with discounting (Pender 1996; Reimers et al. 2009). For example, Tanaka et al. (2010) examine risk and time preferences in Vietnam and find that household income is positively related with patience. However, the effect on present bias is not clear. While Tanaka et al. (2010) find that none of the income variables explain individual differences in present bias, Meier and Sprenger (2010) and Carvalho et al. (2016) find an inverse relationship between income and present bias. Similarly, empirical evidence shows that poverty is positively related with discounting and present bias (Haushofer and Fehr 2014; Bartoš et al. 2021). Poor individuals may not even have the possibility to delay consumption since provision of the present is necessary to experience the future (Godoy and Jacobson 1999). So far nothing is known about the time preferences of households who live with a disabled family member in developing countries where poverty is already an issue.

We argue that households with disabled family members, constitute a subgroup which has not received much attention in economic research yet, and might face adverse economic outcomes. In addition, household disability may raise the household members' awareness of the possibility to experience poor health conditions, disability and mortality in the future. Thus, disability households can be considered as vulnerable and all of these factors are positively associated with discounting. Thus, household disability may increase household members' thoughts about their own, in the future potentially severe health status which can be expected to affect, consciously or unconsciously, how household members evaluate future events. Therefore, we assume that individuals living in a disability households discount the future more intense than individuals that live in non-disability households. In addition, household disability may increase the household members' care-giving responsibilities, mental burden, and level of stress. This additional mental strain to the already high level of mental load of people living in poverty (Bruijn and Antonides 2022) might make it more difficult for individuals to think and imagine the future. Besides the economic pressure to provide for the present, household members of disability households need to organize an inclusive daily routine, e.g. transportation and medical support. Therefore, it is possible that time preferences vary among individuals who live in a disability households and those who do not. We hypothesize firstly that individuals who live in disability households discount the future stronger than individuals that live in non-disability households. Secondly, we hypothesize that individuals living in disability households are more present biased than individuals that live in non-disability households.

New knowledge on varying time preferences of individuals living in disability households, would help to better understand their decision making processes and in turn provides information for public policies how to tackle the adverse living conditions of people in disability households more precisely.
We employ a random sample of 840 individuals living in rural Vietnam, Ha Tinh. In order to reveal time preferences we employ a standard question commonly used in other surveys to measure time preferences. We make use of randomized psychological primes in order to recall a good, neutral or negative health situation within a household, and we reveal time preferences in addition doing an experimental game using multiple price lists with financial rewards.
Our results show that people living in a disability household are more likely to be more patient and more present biased compared to persons living in non-disability households. The results suggest furthermore, that the negative prime amplifies the negative effect. While a higher level of patience could affect long-run economic decisions also positively a greater present bias could outweigh this effect - as both effects running against each other.
Priming has already been used in economics to study (among others) the effect of war and conflict on risk preferences in Afghanistan (Callen et al. 2014), the effect of ethnic, racial, and gender identity norms on time and risk preferences (Benjamin et al. 2010), or the professional identity of bankers on the willingness to take risks (Cohn et al. 2017).
Our paper advances the relevant literature in three ways. First, we contribute to the broader literature on the interrelationship of poverty and disability. A large body of literature focuses on poverty and disability revealing that both are intimately linked, with the one reinforcing the other (Banks et al. 2017; Groce et al. 2011; Palmer 2011). Research shows that the association between disability and poverty is likely mitigated by a number of factors, e.g. education (Filmer 2008; Mont and Cuong 2011; Mont and Nguyen 2013), productivity (Buckup 2009), labor participation (Mitra et al. 2013; Trani and Loeb 2012), and extra costs associated with disability (Braithwaite and Mont 2009; Mitra et al. 2017). One factor, however, has not yet been taken into account which are time preferences. Since time preferences are highly correlated with many future economic outcomes such as educational and occupational choices (Meier and Sprenger 2010), accumulation of wealth (Huffman et al. 2019) and health behavior and health outcomes (Chabris et al. 2008; van der Pol 2011), different time preferences in the disability and non-disability households could be one channel through which household disability affects poverty. Therefore, to the best of our knowledge, this paper is the first one to analyze the effect of disability on time preferences.
Second, we contribute to the strand of literature that elicits time preferences in developing countries. One the one hand, a large body of literature relies on the exponential discounting model to measure time preferences (Voors et al. 2012; Callen 2015; Cassar

et al. 2017; Chantarat et al. 2019; Jetter et al. 2020). However, empirical literature shows that the quasi-hyperbolic model fits the experimental and field data often better than the exponential discounting model (Frederick et al. 2002; Kirby and Maraković 1996; Kirby 1997; Kirby et al. 2002). One the other hand, some experimental studies use structural maximum likelihood estimations to estimate model parameter values of the utility function. The method proposed by Andersen et al. (2008) estimates time and risk preference parameters jointly based on the expected utility theory (e.g. Hermann and Musshoff (2016b), Hermann and Musshoff (2016a) and Wegmann et al. (2021)). The method proposed by Tanaka et al. (2010) estimates six parameters, i.e. risk aversion, loss aversion, probability weighting, time discounting, present bias and a hyperbolicity parameter, based on prospect theory (e.g. Liebenehm and Waibel (2014) and Liebenehm and Waibel (2018)). Both approaches, however, rely on strict model assumptions and estimate global parameters for the whole sample instead of estimating parameters for single participants. Therefore, this paper proposes a method with less restrictive assumptions but that takes long-term discounting and present bias into account. We use the respondents' points of indifference in four multiple price lists (MPLs) to calculate the discount and present bias parameter. To the best of our knowledge, this method has only been implemented in similar forms by Meier and Sprenger (2010) who studied present-biased preferences and credit card borrowing and by Bradford et al. (2017) who studied time preferences and consumer behaviour. This approach is especially effective if the aim is not to estimate utility function parameters but to compare discounting as well as present bias between sub-samples.

Third, we contribute to the broader literature in development economics that sheds lights on the life of people with disabilities. Traditionally, disability and international development have been two separate fields that have only recently started to come together. The international development community recognized that the global development targets cannot be achieved unless disability is treated as a cross-cutting issue (similarly to how gender was mainstreamed over the last years) (Palmer 2011). In addition, we add to the scarce literature on disability that investigates the spillovers of a disability incidence in the household to other household members. In fact, we are only aware of four studies (Bogan and Fernandez 2017; Bratti and Mendola 2014; Powers 2001, 2003) that went beyond descriptive statistics and cross-sectional regressions in this context. While Bratti and Mendola (2014) and Mont and Nguyen (2013) examine the impact of parental disability on children's education outcomes, Bogan and Fernandez (2017) investigate the effect of a child's disability on a household's investment decisions. Similarly, in Powers (2001) and Powers (2003) the author focuses on child disability and looks into its implication for female labor supply. In contrast, our study focuses on a different group (other household members) and outcome (time preferences).[1]

In this regard, we believe that this is one of the first studies on the impact of shocks on time preferences that is able to experimentally elicit short- and long-term discounting and econometric identification strategies to shed light on the same research question within the same context.

The remainder of the paper is structured as follows. Section 2 provides background information on our Data and sampling method, household disability, as well as information on the priming and elicitation of time preferences employed. Section 3 presents the econometric model. Section 4 shows the results on the effect of intra-household and robustness analyses. Section 5 provides a discussion and concludes.

2 Setting and Data Collection

2.1 Data

The survey and experiments were conducted during August and September 2018 in rural areas of the Ha Tinh province in Vietnam.[2] Ha Tinh lies in the northern part of central Vietnam as a costal region. Ha Tinh was selected as study province because among three study provinces we were previously working with (Hue, Ha Tinh and Dak Lak), the share of people with disabilities was slightly higher in Ha Tinh than in the other two provinces.[3] One reason for this could be that Ha Tinh is near the former North-South Vietnam border where the intensity of bombing was the highest during the Vietnam war (Miguel and Roland 2011).

Vietnam is suitable as study ground because most Vietnamese villagers are poor but literate, thus, it is relatively easy to motivate them with moderate financial incentives and to ensure they comprehend the experimental tasks. Moreover, as a consequence of the Vietnam War, disability prevalence but also awareness is increasing and people are familiar with disabilities and disability policies (Palmer et al. 2019; Rohwerder 2018). As a result, disability related questions are not as sensitive as in other countries what leads to easier data collection and higher data quality.

The sampling frame consists of all 160 villages in the Ha Tinh province of which 83 villages were randomly selected. We conducted a household listing exercise in each village. We listed the household size, household head's level of education and the wealth level for each household as well as an indicator if the household includes

[1] Traditionally, studies in health economics have focused on illnesses and chronic diseases. Regarding disability, a more developed literature examines the impact of disability onset on the disabled person's own socio-economic outcomes (Bjorvatn and Tungodden 2015; Mitra and Sambamoorthi 2008; Mitra et al. 2009; Oster et al. 2013; Singleton 2012; Stephens 2001; Stern 1989; Mani et al. 2018; Meyer and Mok 2019).

[2] For more information on the risk preference experiment see Priebe et al. (2019).

[3] The information on the share of disability households by province was obtained from official statistics as well as from the Thailand Vietnam Socio Economic Panel.

PWDs.[4] The disability status was cross-checked by a field team that conducted the household visits. Based on the list, an equal share of disability households[5] and of non-disability households for each village was randomly selected stratified by household size and household head's level of education. In total, 804 households were sampled. Since the number of disability households was not constant across villages, the number of participants varies at the village level. Between 10 and 38 persons from one village participated in the experiment. The experiment was conducted with the household heads. If the head was unavailable, the experiment was conducted with the spouse or another adult household member. Prior to any individual visit, all sampled households were randomized into one of the three priming groups.[6]

The lab-in-the-field experiment was conducted in the participants' home. After informing the participants about the confidentiality of the data, the experimenter conducted a short interview asking for demographic and socio-economic characteristics, as well as for the respondents' well-being, risk preferences and personality traits. The experiment was incentivized by paying participants in accordance with their expressed preferences. Therefore, the experimenter provided the participant with details of the potential earnings, including the possibility of cash payments.

Time preferences were revealed threefold: first, by a non-incentivized survey question asking the respondent to make four binary choices between 60 Million Dong today and 60 (120, 180 and 240 respectively) one year later, second, by multiple price lists where the respondent could make six binary choices either receiving a certain amount today or in five weeks, third the same but with the time extension of nine weeks (see section 2.3 for a detailed description of the elicitation of the time preferences).

Directly before the start of the experiments, each participant was exposed to a priming session according to its priming group. Upon completion of the experimental tasks, one decision was selected at random for payment by flipping a coin. If the time preference game was selected, the participants received the rewards that they chose on that question in the number of weeks specified. Immediate rewards were paid in private and average earnings were 135,000 Vietnamese Dong (VND) (approx. 5.77 US-Dollar). Future rewards were paid out through the participants' mobile phone accounts. The rational of incentivizing experiments is that subjects truthfully reveal their preferences. The payment approximately corresponds to the wage for one full day of agricultural labor and thereby should offset the opportunity cost of participating. From instructions to payoff, the sessions took between 45 to 70 minutes.[7]

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4 To avoid asking people directly about their disability status which often identifies only persons with the most severe disabilities (Mont 2007), village officials conducted this exercise. To achieve a consistent listing across villages, they were trained with disability concepts (WHO 2011; WG 2017).

5 Households whose head is disabled were excluded.

6 Section 2.3 addresses the method of priming in more detail.

7 The whole questionnaire including the experiments can be obtained upon request.

Table 1: Summary Statistics: Disability Sample

	Mean	Median	SD	Min.	Max.	Obs.
Age of PWD (years)	48.08	52.00	17.11	1.00	95.00	296
PWD is female	0.35	0.00	0.48	0.00	1.00	290
PWD is married	0.66	1.00	0.48	0.00	1.00	296
PWD compl. primary educ. or less	0.32	0.00	0.47	0.00	1.00	296
PWD compl. junior secondary educ.	0.48	0.00	0.50	0.00	1.00	296
PWD compl. secondary educ. or higher	0.17	0.00	0.38	0.00	1.00	296
Disabled is hired labor	0.17	0.00	0.37	0.00	1.00	296
Disabled is not working	0.74	1.00	0.44	0.00	1.00	296
Person has very severe disability	0.36	0.00	0.48	0.00	1.00	296
Person has severe disability	0.43	0.00	0.50	0.00	1.00	296
Person has moderate disability	0.18	0.00	0.39	0.00	1.00	296
Physical disability	0.83	1.00	0.38	0.00	1.00	296
Years since person has disability	14.88	9.00	14.94	0.00	69.00	291
Years since impairments are serious	11.19	6.00	13.19	0.00	66.00	294
Multiple disability HH	0.10	0.00	0.30	0.00	1.00	296
Age (years) at onset of disability	33.07	32.00	21.79	0.00	90.00	291
Recent disability	0.41	0.00	0.49	0.00	1.00	296

2.2 Disability Households

Although we consider disability households as a unit, differences among persons with a disability should be considered as well because these characteristics are also reflected in the household. For instance, if a younger household member has a severe disability intra-household decisions and behaviors of household members might be different as compared to a moderate disability among the elderly household member. Thus, PWDs are not a homogeneous group. They differ in disability-related characteristics that might mediate the effect of the disability on household members' time preferences. The age at onset of the disability varies in our sample. There is much heterogeneity ranging from birth to the age of 90. For about one third of PWDs, the disability started between birth and the age of 18. A disability in this age likely affects individuals' educational and vocational formation and thereby, their occupational opportunities.[8]
Table 1 shows the summary statistics of our disability sample. The average age of the person in the household who has a disability is 48, 35 percent are female and 66 percent males. 32 percent completed primary occupation and 17 percent have a secondary or a higher degree. On average a person has a disability since 14.8 years. The average age of the disability onset is 33.
The severity of disability varies in our sample as well. The majority of PWDs is not able to work (72 percent), which is positively correlated with the severity of impairment. Figure 1 shows the share of PWDs that has a physical versus mental disability across

[8] The number of years the PWD has a disability is rather low, indicating that a sizable portion of PWDs in our sample acquired rather recently a disability. Descriptive statistics on the distribution of the onset of the disability can be obtained upon request.

Figure 1: Type and Severity of Disability

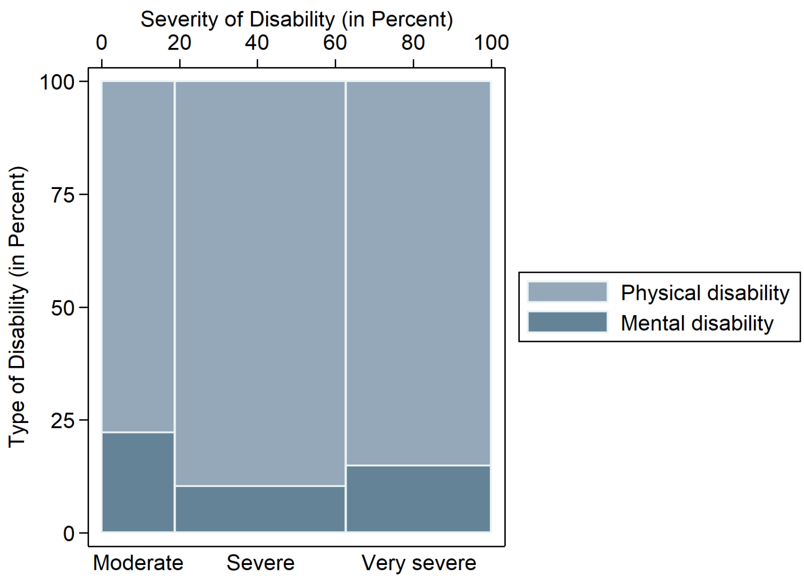


Table 2: Reasons for Disability

	Frequency	Percent
Old age	2	0.68
Intoxication/Agent Orange	5	1.69
Congenital defects	8	2.70
War	10	3.38
Other accident	14	4.73
Road accident	25	8.45
Work accident	29	9.80
Untreated illness	80	27.03
Chronic disease	102	34.46
Other	21	7.09
N	296	100.00

the severity status of disability. The majority of PWDs has a severe physical disability (43 percent), followed by a very severe (36 percent) and moderate physical disability (18 percent).
Table 2 presents the reasons for the disability. Around 61 percent say its due to an illness either untreated or chronic. Thereafter, accidents, either road, work or other accidents, jointly account for about 23 percent of the reasons. War and intoxication, e.g. Agent Orange, jointly account for five percent. Looking at the reasons why and to what extent people have a disability reveals that the impairment in everyday life and thus, the burden for the household members can be expected to be high and a chronic disease can also be a (long-term) consequence of the Vietnam war (Miguel and Roland 2011).

2.3 Priming

Although descriptive statistics show that a good share of disability in our sample is due to an accident, which could be considered as exogeneous, a comparison of time preferences of both groups would yield to biased results. It could be possible that the causal relationship goes the other direction and individual time preferences have an effect on disability, i.e. through reverse causality. For instance, individuals who are not willing to delay gratification might not support the preventive health behavior of their household members which yields future returns. This link is particularly relevant in case of the parent-child relationship. Descriptive statistics show that a sizable share of respondents state as reason for the disability "untreated illness". Furthermore, disability is rather not random because there are many factors that increase the likelihood of becoming disabled such as poverty, risky working conditions, and health behavior. As a result, it could be that unknown and unobserved factors influence both individual time preferences and the household members' disability status. Since it is impossible to observe all of the potential confounding factors, an omitted variable bias is likely to occur. Experimental and random administration of disabilities would solve these problems but it is clearly not feasible. Therefore, the experiment includes randomized disability-related primes to exogenously manipulate the intensity of disability-related thoughts, feelings and mindsets, i.e. the disability environment. Thus, instead of experimentally administer disability, it is experimentally recalled.
A prime is a subtle stimulus that activates a related mental representation that influences other, i.e. semantically, lexically or perceptually, related mental representations. The stimulus can either be a word, sight, smell or sound. A priming effect occurs when an individual's exposure to a stimulus influences his or her response to a subsequent stimulus without that individual being aware of the link (Doyen et al. 2014).
Similar to Callen et al. (2014), Lerner and Keltner (2001), and Lerner et al. (2003) the experimental design includes three distinct priming schemes: negative, positive and

neutral. Similar to Bjorvatn and Tungodden (2015) the negative, disability-related is the principal priming scheme. One third of respondents were randomly exposed to this priming scheme that was designed to stimulate the mental representations of disability and the associated living conditions. Therefore, it includes key words such as "sick", "stigmatization", "loses the job", "hurt" and "assistance". In contrast, the positive primes include key words such as "happy", "joy" and "satisfaction". The neutral primes did not include any of such keywords. Therefore, respondents that were exposed to the neutral primes form the control group. With the two treatments, i.e. negative versus positive primes, it can be investigated if the responses to the primes are generally driven by emotions.

For instance, our negative prime was addressed as follows: *We are interested in understanding your daily experiences that make you fearful or anxious about your family. This could be anything that refers to other family members. For example, if someone gets sick, experiences violence, loses the job, etc. Could you describe an event in the past year that caused you fear or anxiety about another family member?*

Through randomization, priming can establish causality where randomized controlled trials would be too costly, ethically unacceptable, or simply not feasible (Cohn and Maréchal 2016). The key identifying assumption necessary to be able to measure the causal effect of the disability environment on individual time preferences is that the primes change the relative weight of the saliency of the disability environment at the moment of the experiment. If this assumption is met, any difference in discounting and present bias between the priming groups reveals the disability environment's marginal effect.

In economic experiments, priming typically includes actively prompting subjects to think about a specific concept or past experiences to activate the related mental representation (Cohn et al. 2015). This can be done by using lexical priming, e.g. using a list of words that the participant needs to reorganize and make a senseful sentence, i.e sentence scramble tasks (Bargh et al. 1996; Tory Higgins et al. 1977), or word puzzles (Bargh et al. 2001); verbal priming such as storytelling (Callen et al. 2014) and answering a short questionnaire; audio-visual priming, e.g. using pictures (Vohs et al. 2006), videos and music (North et al. 1999) as well as more implicit approaches through odors (Holland et al. 2005), temperatures (Williams and Bargh 2008) and subliminal stimuli (McKay et al. 2011; Andersson et al. 2017). These different approaches come with various advantages and challenges, especially in a developing country context.[9]

The advantage of implicit approaches is that participants are unlikely to recognize the prime and, thus, it can be assumed that the priming mechanism works automatically. However, it comes with the issue that the prime is too implicit not causing any re-

[9] To the best of our knowledge, only Cohn et al. (2015) reviewed priming as a method in (experimental) economics but they do not explicitly address the implementation of priming in developing countries.

sponse. The verbal priming circumvent the above-mentioned challenges. However, the effectiveness of the verbal primes might depend on how the primes are presented to the participant, e.g. the height of the voice and pronunciation.

Therefore, our experimental design includes verbal primes and follows closely the set-up in Bjorvatn and Tungodden (2015) who employ priming to investigate the effect of social identity on disabled secondary school students in Uganda as well as in Callen et al. (2014), whose primes involve storytelling. As priming has been found to have short-term effects, respondents were primed twice with the same priming scheme as in Bjorvatn and Tungodden (2015).[10] Similar to Benjamin et al. (2010) and Bjorvatn and Tungodden (2015) the second prime consisted of answering a short questionnaire.

Despite the advantage of inducing exogenous variation, priming comes with challenges. For instance, previous research has shown that a priming effect can be biased if participants are aware of the aim of the primes causing an experimenter demand effect (Benjamin et al. 2016). The reason is that when priming becomes conscious, people tend to correct their behavior. To assess whether respondents understood that the negative primes were designed to make them think of the disability environment, individuals participating in the pre-tests, i.e. including individuals with and without a disabled household member, were asked: "What do you think we are trying to find out by these questions?". None of the answers suggested that the participants linked the primes to a disability incidence in their household.

Moreover, there is no consensus on the exact mechanisms responsible for the priming effects in social psychology. The traditional theory suggests that the spreading activation model from cognitive psychology can also explain priming of more complex social and goal directed behavior (Collins and Loftus 1975; Bargh et al. 2001). Cognitive psychologists, however, argue that the influence of a prime is rather weak and lasts merely seconds in contrast to the large and longer-term priming effects found by social psychologists and economists (Jonas 2013; Cesario and Jonas 2014). Modern theories of priming suggest that the activation of an individual's mental construct is not the sole influence on their decision. Due to the variety of the priming effects, scholars propose numerous models and a set of moderators that try to explain the prime-to-behavior effects (see Wheeler and DeMarree (2009) for a review and Bargh and Chartrand (2014) provide a guide to priming).

[10] There was no variation in terms of priming groups within subjects, e.g. if a respondent was randomized into the neutral group, the person received only neutral primes.

Table 3: Balance of Sample Characteristics across Priming Groups

	(1) Neutral	(2) NP	(3) PP	(4) (1) vs. (2), p-value	(5) (1) vs. (3), p-value	(6) (2) vs. (3), p-value
Age of respondent	51.082	51.192	51.372	0.922	0.784	0.875
	(0.730)	(0.852)	(0.763)			
Female respondent	0.588	0.616	0.606	0.541	0.697	0.825
	(0.032)	(0.033)	(0.033)			
Married respondent	0.860	0.849	0.863	0.743	0.932	0.685
	(0.022)	(0.024)	(0.023)			
Resp. HH head	0.728	0.676	0.712	0.217	0.700	0.403
	(0.029)	(0.032)	(0.030)			
Primary educ.	0.218	0.196	0.199	0.566	0.614	0.942
	(0.027)	(0.027)	(0.027)			
Junior secondary educ.	0.551	0.630	0.588	0.086	0.419	0.369
	(0.032)	(0.033)	(0.033)			
Secondary educ.	0.230	0.174	0.212	0.130	0.639	0.300
	(0.027)	(0.026)	(0.027)			
Household size	4.008	4.005	3.795	0.980	0.125	0.166
	(0.098)	(0.116)	(0.098)			
General health status	3.592	3.637	3.609	0.365	0.728	0.566
	(0.035)	(0.035)	(0.034)			
Subjective wealth	2.580	2.562	2.686	0.849	0.309	0.219
	(0.071)	(0.066)	(0.076)			
Respondent migrated to the village	0.370	0.397	0.376	0.554	0.898	0.648
	(0.031)	(0.033)	(0.032)			
Respondent migrated to the subdistrict	0.189	0.183	0.230	0.855	0.279	0.218
	(0.025)	(0.026)	(0.028)			
Respondent years since living in study village	39.453	39.434	39.650	0.990	0.893	0.891
	(1.034)	(1.197)	(1.032)			
Patience scale	6.370	6.352	6.327	0.940	0.865	0.926
	(0.171)	(0.183)	(0.187)			
Patient decision	2.560	2.425	2.496	0.347	0.650	0.620
	(0.100)	(0.102)	(0.099)			
Willing to take risk	5.860	5.913	5.973	0.832	0.644	0.813
	(0.171)	(0.183)	(0.176)			

Notes: Standard errors are in parentheses. “Neutral” means neutral prime, “NP” means negative prime “PP” indicates positive prime. The column (4) reports the p-values for the t-test of group differences neutral vs. negative prime (5) neutral vs. positive and (6) negative vs. positive.

Table 3 shows descriptive statistics of our sample across priming groups. The table shows that the sample is balanced across treatment groups in all dimensions such as e.g. gender, age, education, but maybe most importantly also in the general health status of the respondents. Since disability is not random, pre-existing differences in time preferences between the disability and the non-disability households could affect the experimental choices. However, the results from two-sided t-tests reveal that the null hypothesis of equal means cannot be rejected at conventional significance levels for each of the two pre-prime time preferences measures (p-value=0.81 for *Patient decision* and p-value=0.2 for *Patience scale*). These results increase the confidence that experimental effects on time preferences are the result of the administration of primes and do not reflect pre-existing difference.

2.4 Elicitation of Time Preferences

The basic experimental design for eliciting time preferences was introduced by Coller and Williams (1999) and expanded by Harrison et al. (2002). The so-called multiple price list (MPL) experiment consists of monetary choices that are shown in Table 5. For example, the participant was asked "Would you prefer to receive VND 150,000 today or VND 180,000 in 5 weeks?".[11] The larger later (LL) reward was kept constant at VND 180,000 whereas the smaller sooner (SS) reward decreased monotonically from VND 150,000 to VND 30,000.

Each participant answered four different MPLs with six questions each and, thus, each participant had to make 24 monetary choices in total. In MPL1 (MPL2), participants made six binary choices between receiving a SS reward today and receiving VND 180,000 in five weeks (nine weeks). In MPL3 (MPL4) participants made six binary choices between a SS reward in five weeks and receiving VND 180,000 in 10 weeks (14 weeks). Thus, MPL3 and MPL1 as well as MPL4 and MPL2 measure the attitudes towards an identical delay with and without front-end delay. The front-end delay in MPL3 and MPL4 tries to avoid the potential problem of facing extra risks or transaction costs associated with the future reward, as compared to the instant income option. For example, these extra costs include participants' concerns about whether they would receive the delayed rewards. If only the delayed option includes such costs, then the elicited implicit discount factors would include these subjective transaction costs, too. However, by having both options presented as future rewards, these costs are hold constant (Andersen et al. 2008). The elicited implicit discount factors can be interpreted as applying to a time delay of five and nine weeks, respectively.

The MPL task measures parameters of a discounting model at the individual level. Since empirical studies find that a quasi-hyperbolic model explains real-world discounting

[11] At the time the survey was conducted (August, 31 2018) the nominal exchange rate was 23,287.91 VND $\approx$ 1 USD (Exchange-rate.org 2022).

behavior better than exponential discounting, the four MPLs are used to calculate parameters of a quasi-hyperbolic discount function. The discount parameters are not estimated by fitting a quasi-hyperbolic function to the data, but are determined by subjects' switching points between the SS and the LL rewards, i.e. points of indifference. Critical points for each participant and each MPL are defined, where the participant switches from choosing the SS to the LL reward. For instance, an individual prefers VND 150,000 today to VND 180,000 five weeks later in MPL1, but prefers VND 180,000 five weeks later to VND 135,000 today in the next question. Then, the critical points are VND 150,000 and VND 135,000. Switching between these two questions implies that the subject is indifferent at some point along the interval of VND 150,000 and VND 135,000. We then take the average of these critical points and assume to be the level of payment that would steer indifference between the earlier and the later option, e.g. indifference between VND 142,500 today and 180,000 five weeks later. For the participants that switch in the first or last row, we also assume that they are indifferent between the SS and LL reward.

In a two periods scenario, the discount factor between today and the next period is given by $SS = \beta \times \delta^{D} LL$ and between two future periods by $SS = \delta^{D} LL$, where $0 < \beta < 1$ measures the degree of present bias and $0 < \delta < 1$ is the discount factor. If the participants are not present biased, β equals one and δ equals the exponential discount factor. D measures the delay of five and nine weeks, respectively. Applying the equation to the four MPLs yields four equations with in total four unknown parameters:

$$SS_{MPL1} = \beta_1 \delta_1 LL_{MPL1} \tag{1}$$

$$SS_{MPL2} = \beta_2 \delta_2 LL_{MPL2} \tag{2}$$

$$SS_{MPL3} = \delta_1 LL_{MPL3} \tag{3}$$

$$SS_{MPL4} = \delta_2 LL_{MPL4} \tag{4}$$

Thus, Equations 3 and 4 reveal δ_1 for a delay of five weeks and δ_2 for a delay of nine weeks, respectively. Inserting them in Equations 1 and 2, respectively, yields β_1 for a delay of five weeks and β_2 for a delay of nine weeks. Thus, β_1 and β_2 are equivalent to $\frac{\delta_1}{\delta_3}$ and $\frac{\delta_2}{\delta_4}$, respectively. To summarize, four parameters $(\delta_1, \delta_2, \beta_1, \beta_2)$ are calculated for each participant.

Table 4 shows the Spearman Rank Correlation Coefficient among our parameters. Here we see that β_1 and β_2 are negatively and $Pb1$ and $Pb2$ are positively correlated with all discounting measures. Thus, more patient individuals seem to be more present biased.

Table 4: Spearman Rank Correlation Coefficients across Time Preference Measures

	Patient decision	Patience scale	IDF1	IDF2	Beta1	Beta2	Pb1
Patience scale	0.19						
	(0.00)						
IDF1	0.25	0.14					
	(0.00)	(0.00)					
IDF2	0.27	0.11	0.70				
	(0.00)	(0.01)	(0.00)				
Beta1	-0.03	-0.06	-0.72	-0.42			
	(0.51)	(0.13)	(0.00)	(0.00)			
Beta2	-0.04	-0.07	-0.43	-0.65	0.56		
	(0.31)	(0.10)	(0.00)	(0.00)	(0.00)		
Pb1	0.11	0.06	0.78	0.51	-0.91	-0.51	
	(0.01)	(0.17)	(0.00)	(0.00)	(0.00)	(0.00)	
Pb2	0.11	0.08	0.52	0.72	-0.52	-0.92	0.54
	(0.01)	(0.05)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Notes: Summary statistics are based on the sample of 688 households. P-values in parentheses.

Unsurprisingly, $Pb1$ and $Pb2$ are negatively correlated with β_1 and β_2 with a high and statistically significant correlation between variables measuring (the intensity of) present bias for an identical delay.

Two key identifying assumptions must be fulfilled to measure the implicit discount factor and present bias parameter. First, it is assumed that utility is linear in money. Monetary payments at date t are assumed to generate a VND-equivalent incremental consumption event with the corresponding utility flow at time t. Thus, participants are assumed to consume the payments at the time of receipt and do not smooth consumption nor participate in arbitrage, e.g. investing the immediate rewards at time t (Cohen et al. 2020). For this sample, this assumption is likely to hold because first, participants are poor and the size of the rewards are modest. Thus, they most likely consume the rewards instantly and do not integrate them in their consumption stream. Second, some scholars argue that experimental rewards are not integrated in individuals' background consumption because participants use different mental accounts for the experimental rewards and their background consumption (Andersen et al. 2008). Third, the individuals in this sample are unlikely to have access to perfect capital markets nor knowledge of the rates of return that at the time of the experiment would apply to them (Coller and Williams 1999; Harrison et al. 2002).[12]

The second assumption is that the utility function is locally linear. This may arise because the utility function is globally linear (and the individual is risk neutral) or because background consumption is large and the utility function has diminishing absolute risk aversion, e.g. constant relative risk aversion (Cohen et al. 2020). Since the

[12] This assumption is also supported by the general large number of borrowing and lending opportunities in the field as well as the volatility and variability of the associated rates of return as explained in Coller and Williams (1999, p. 110) and Harrison et al. (2002, pp. 1607-1609).

rewards in the experiments are sufficiently small, the assumption of linearity is likely innocuous. Nevertheless, individual risk preferences will be included as a control variable in the regression analysis since it has been shown that measuring time preferences without controlling for risk preferences can lead to biased results (Andersen et al. 2008; Andreoni et al. 2015).

2.5 Time Preferences and Treatment Groups

Table 5 lists the implied discount factors for a respondent who is just indifferent between the SS and LL rewards, along with the percentage of respondents choosing the LL reward. For instance, in the first row, a respondent who is just indifferent between VND 150,000 today and VND 180,000 in five weeks has a five-week discount factor of 0.8333, and 9.12 (4.59) percent of respondents of the disability (non-disability) sample chose VND 180,000 in five weeks over VND 150,000 today. The 5th and 6th column of Table 5 show the proportion of respondents that choose the LL reward for each question in the MPLs. We see that respondents choose the SS reward for a number of questions and switch to the LL reward for the remainder. This behavior is observed for the disability and the non-disability sample. For each MPL, the percentage share of choosing the delayed reward increases as the earlier reward decreases. However, between five and nine percent already choose the LL reward in question one in the first two MPLs what indicates an extremely high level of patience. Nevertheless, the majority of the participants still chooses the SS reward for the last question which reveals an extremely high level of impatience. For each question, there are more individuals choosing the LL reward in MPL3 than in MPL4. Thus, respondents are more patient for a delay of five than for a delay of nine weeks.

Comparing the shares for MPLs with and without front-end delay reveals that more participants choose the LL reward already in the first question in MPLs with front-end delay (MPL3 and MPL4). This suggests that the participants are present biased since they are more patient if the choices do not include an immediate option. Overall, the respondents are more present biased for a delay of five than for a delay of nine weeks. The only difference in choice pattern between the disability and the non-disability sample is that there are more respondents in the disability sample sample that choose the LL reward compared to the non-disability sample for each question in all four MPLs. Thus, respondents in the disability sample are more patient than respondents in the non-disability sample as long as there is not immediate option (e.g. today).

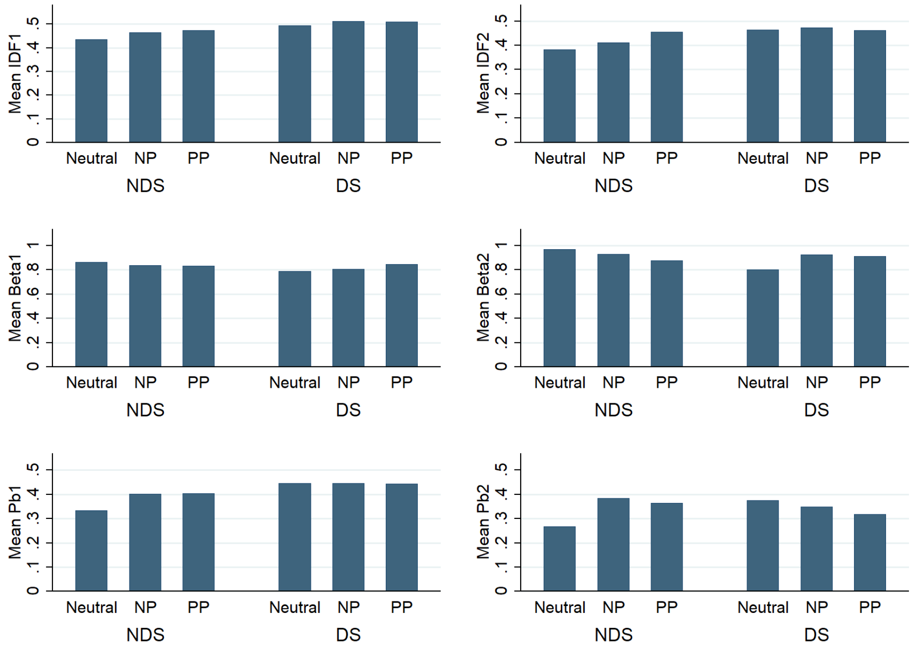
Figure 2 presents the mean values for the experimental time preference measures across the disability and non-disability sample and priming groups. For *IDF1*, there is a small difference between the disability and the non-disability sample. The primes, however, do not seem to have a significant effect on *IDF1*. However, the mean values are higher for the positive and negative primed respondents compared to the neutral primed

Table 5: Choice Trials and their associated Discount Factors

MPL	Choice Trial	Delay	Discount Factor	%LL	
				Disability	**Non-disability**
1.1	150,000 today or 180,000 in 5 weeks	5	0.8333	9.12	4.59
1.2	135,000 today or 180,000 in 5 weeks	5	0.7500	12.16	7.40
1.3	120,000 today or 180,000 in 5 weeks	5	0.6667	14.19	11.99
1.4	100,000 today or 180,000 in 5 weeks	5	0.5556	21.96	16.58
1.5	72,000 today or 180,000 in 5 weeks	5	0.4000	32.43	26.28
1.6	36,000 today or 180,000 in 5 weeks	5	0.2000	38.85	33.67
2.1	180,000 today or 180,000 in 9 weeks	9	1.0000	5.07	3.06
2.2	150,000 today or 180,000 in 9 weeks	9	0.8333	7.77	5.10
2.3	120,000 today or 180,000 in 9 weeks	9	0.6667	13.22	9.44
2.4	90,000 today or 180,000 in 9 weeks	9	0.5000	28.04	22.45
2.5	60,000 today or 180,000 in 9 weeks	9	0.3333	32.43	28.13
2.6	30,000 today or 180,000 in 9 weeks	9	0.1667	41.55	35.46
3.1	150,000 in 5 weeks or 180,000 in 10 weeks	5	0.8333	31.08	24.49
3.2	135,000 in 5 weeks or 180,000 in 10 weeks	5	0.7500	33.78	29.59
3.3	120,000 in 5 weeks or 180,000 in 10 weeks	5	0.6667	38.51	33.93
3.4	100,000 in 5 weeks or 180,000 in 10 weeks	5	0.5556	49.66	41.33
3.5	72,000 in 5 weeks or 180,000 in 10 weeks	5	0.4000	57.77	49.74
3.6	36,000 in 5 weeks or 180,000 in 10 weeks	5	0.2000	64.19	54.22
4.1	180,000 in 5 weeks or 180,000 in 14 weeks	9	1.0000	11.82	8.42
4.2	150,000 in 5 weeks or 180,000 in 14 weeks	9	0.8333	18.58	14.03
4.3	120,000 in 5 weeks or 180,000 in 14 weeks	9	0.6667	28.04	21.99
4.4	90,000 in 5 weeks or 180,000 in 14 weeks	9	0.5000	44.59	38.27
4.5	60,000 in 5 weeks or 180,000 in 14 weeks	9	0.3333	54.73	46.68
4.6	30,000 in 5 weeks or 180,000 in 14 weeks	9	0.1667	58.78	49.74

Notes: The discount factor is the value at which the immediate and delayed rewards are of equal value. Delay is the difference between the time of the LL and SS reward and is measured in weeks. The discount factors are measured for the delay of five and nine week, respectively. All rewards are in VND. The last two columns show the percentage of respondents choosing the delayed reward on each question.

Figure 2: Averages of Time Preferences Outcomes over Treatment Groups



respondents. For *IDF2*, the mean values are much larger in the non-disability sample for the positive primed compared to the negative and neutral primed respondents. However, the mean values for *IDF2* are similar across priming groups in the disability sample. For *Beta1*, the mean values are smaller for the negative and positive primed in the non-disability sample. The opposite is true for the disability sample. Similar effects can be observed for *Beta2*, however, on a generally higher level. For the binary variable *Pb1* the positive and negative primes increase the mean values for the non-disability sample but have no effect on the mean values for the disability sample. For the binary variable *Pb2* the positive and negative primes increase the mean values for the non-disability sample but decrease the mean values for the disability sample.
This descriptive analysis reveals that the disability household is more present biased and patient than the non-disability household. The primes seem to affect time preferences and the effect seems to be larger for present bias than for discounting factors. We see an overall priming effect. The next section uses a multivariate framework to incorporate simultaneity of various confounds.

3 Model

We employ a multivariate regression model to identify the effect of household disability on respondents' time preferences controlling for potential confounding factors as in equation 5.

$$T_{iv} = \beta_0 + \beta_1 DS_{iv} + \beta_2 NP_{iv} + \beta_3 DS_{iv} \times NP_{iv} + \beta_4 PP_{iv} + \beta_5 DS_{iv} \times PP_{iv} + \phi PRE_{iv} + \phi X'_{iv} + \alpha_s + \epsilon_{iv} \quad (5)$$

Outcome variables are the time preferences T of respondent i in village v. More precisely, the equation is estimated separately for the outcome variables *IDF1*, *IDF2*, *Beta1*, *Beta2*, *Pb1* and, *Pb2*. DS_{iv} is a binary variable indicating whether the respondent is part of the disability sample.

Since disability is not random, the aim of the randomized negative primes was to make the disability environment more salient when making the choices in the experiment. Therefore, NP_{iv} is a binary variable equal to one if the respondent was exposed to a negative prime and zero otherwise. In order to investigate the effect of the positive prime on the respondents' time preferences, we include PP_{iv} which is a binary variable and equal to one if the respondent was exposed to a positive prime and zero otherwise. PRE_{iv} measures the respondents' pre-prime time preferences and should increase the confidence that the experimental effects on time preferences are the results of the administration of primes and do not reflect pre-existing difference. X'_{iv} are the individual and household level control variables. Specifically, these are individual characteristics of the respondent's gender, age, education, marital and health status, subjective wealth, risk preferences and a binary variable for the household head as well as a continuous variable for the household size. α_s are the sub-district fixed effects. The coefficient of interests are β_3 and β_5 measuring the treatment effect of the negative and positive primes, respectively, across the disability and the non-disability sample.

We estimate Ordinary Least Square (OLS) for all six outcome variables. The calculated discounting parameters (*IDF1*, *IDF2*, *Beta1*, and *Beta2*) are bounded at the extremes. As a result, observations for which the respondents switch directly in the first question are left-censored and observations in which respondents never switch are right-censored. For these observations, the calculated parameters could be inaccurate. Thus, the dependent variables (except the binary variables) are left- and right-censored. Therefore, the regression equation is additionally estimated using the Tobit regression model to account for the censored nature of the data. In addition we estimate Probit models for the binary outcome variables *Pb1* and *Pb2*.

4 Results

Table 6 shows the regression results for equation (5). The number of observations varies depending on the outcome variable since the number of inconsistent choices varies across MPLs and the different outcomes are based on different MPLs. All regressions include basic controls and sub-district fixed effects. Standard errors are clustered at the village-level to account for auto-correlated standard errors.[13] Column (1) to (4) show that the respondent of a disability household is on average significantly more patient compared to the respondent of a non-disability household. The effect is statistically significant at the five and ten percent significance level depending on the specification. The effect is larger in the Tobit than in the OLS specifications suggesting that the censored nature of the outcomes affects the size of the estimated coefficients which is not taken into account by OLS. For example, column one shows that the average respondent in the disability sample has an *IDF1* that is 0.07 units larger compared to the average respondent in the non-disability sample. The estimated coefficients are larger for *IDF2* than for *IDF1*. Thus, the average respondent in the disability sample is more patient than the average respondent in the non-disability sample and the difference is larger for a delay of nine than for a delay of five weeks. The negative coefficients of *DS* in column (5) to (8) show that the disability sample is on average more present biased than the non-disability sample. Depending on the specification, the coefficients are statistically significant at the five, ten or one percent significance level. Similarly, the positive coefficients of *DS* in column (9) to (12) show that the average respondent in the disability sample has a higher likelihood to be present biased. However, only the coefficient in the probit regression on *Pb1* is statistically significant at the ten percent level.

The coefficients for *NP* are relatively small and insignificant across most specifications. The coefficient is only statistically significant for the outcome *Pb2*. The OLS regression reveals that respondents that received the negative prime are on average 10.5 percentage points more likely to be present biased for a delay of nine weeks compared to respondents that received the positive or neutral prime. The effect is even larger in the probit specification. The probability that a respondent is present biased for a delay of nine weeks increases by 31.6 percentage points if the respondent received the negative prime compared to respondents that received the positive or neutral prime.

The interaction term of *DS* and *NP* is small and insignificant in all regression specifications. The only exception is *Beta2* and *Pb2* for which the coefficient is large but statistically insignificant. For example, Column (12) shows that respondents' likelihood to be present biased decreases by 34.9 percentage points if the respondent received the negative prime and lives in a disability household, compared to the average respondent in the non-disability household that received the negative prime.

Generally, the coefficients for *PP* are larger in absolute terms than for *NP*. For the

[13] OLS assumes independent and identically distributed standard errors which is equivalent to no auto-correlation between error terms. Since the sample is drawn through a two-stage sampling procedure, the assumption of no auto-correlation is not credible. The data is grouped in villages, sub-districts and districts. Thus, errors are likely to be correlated within the groups due to similar conditions and shocks. Therefore, the number of independent observations equals number of groups, i.e. cluster. Not accounting for the violation of the assumption underestimates standard errors.

outcome *IDF2*, the coefficients for *PP* are statistically significant at the five percent significance level. Thus, receiving the positive primes increases the *IDF2* by 0.07 units in the OLS and 0.13 units in the tobit specification. For the outcome *Pb2*, the coefficient for *PP* is only statistically significant at the ten percent significance level in the probit regression. Thus, receiving the positive primes increases the likelihood to be present biased by 27.5 percentage points compared to receiving the negative or neutral prime. It reveals that receiving a positive prime makes the average respondent more patient and more likely to be present biased. Surprisingly, even though most of the coefficients of *PP* and *NP* are not statistically significant, their coefficients have the same sign. This supports the observation made in the previous section that the effect of both primes goes in the same direction.

The coefficients for the interaction term measuring the treatment effect of the positive primes across the disability and non-disability sample are small, negative and insignificant for *IDF1*. For *IDF2*, however, the coefficients are negative and statistically significant at the ten percent significance level. The coefficients are positive for *Beta1* and *Beta2* but the coefficients are only statistically significant in the regression for *Beta2*. For the binary outcomes *Pb1* and *Pb2*, the coefficients are negative and economically sizable. However, the coefficients are only statistically significant at the ten percent (OLS) and five percent (probit) significance level in the regressions on *Pb2*. Respondents in the disability sample that received the positive prime have on average an IDF that is 0.18 units smaller, are on average 0.25 units less present biased and 51.7 percentage points less likely to be present biased for a delay of nine weeks compared to respondents in the non-disability sample that received the positive prime. The effect size is surprisingly large. The opposite sign for *Beta1* and *Beta2* compared to *Pb1* and *Pb2* is reasonable because positive coefficients for *Beta1* and *Beta2* imply that the intensity of present bias decreases and negative coefficients for *Pb1* and *Pb2* imply that the likelihood to be present biased decreases. Overall, primes have a significant effect for time preference outcomes for a delay of nine weeks.

Table 6: The Impact of Priming: Main Results

	IDF1		IDF2		Beta1		Beta2		Pb1		Pb2	
	OLS	Tobit	OLS	Tobit	OLS	Tobit	OLS	Tobit	OLS	Probit	OLS	Probit
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
DS	0.072	0.095	0.102	0.183	-0.118	-0.118	-0.219	-0.236	0.119	0.341	0.097	0.294
	(0.039)*	(0.049)*	(0.041)**	(0.074)**	(0.060)*	(0.058)**	(0.085)**	(0.089)***	(0.074)	(0.198)*	(0.070)	(0.196)
NP	0.024	0.038	0.023	0.045	-0.041	-0.041	-0.030	-0.031	0.042	0.111	0.105	0.316
	(0.035)	(0.043)	(0.038)	(0.074)	(0.050)	(0.047)	(0.086)	(0.086)	(0.066)	(0.185)	(0.056)*	(0.160)**
Disability sample x NP	0.005	-0.004	-0.016	-0.033	0.079	0.079	0.166	0.174	-0.045	-0.129	-0.119	-0.349
	(0.052)	(0.064)	(0.057)	(0.102)	(0.087)	(0.084)	(0.132)	(0.134)	(0.095)	(0.253)	(0.100)	(0.273)
PP	0.026	0.039	0.069	0.130	-0.025	-0.025	-0.073	-0.088	0.071	0.205	0.087	0.275
	(0.037)	(0.046)	(0.034)**	(0.061)**	(0.067)	(0.064)	(0.083)	(0.085)	(0.072)	(0.197)	(0.059)	(0.166)*
Disability sample x PP	-0.009	-0.009	-0.102	-0.181	0.105	0.105	0.229	0.253	-0.091	-0.261	-0.170	-0.517
	(0.054)	(0.069)	(0.054)*	(0.093)*	(0.109)	(0.104)	(0.123)*	(0.127)**	(0.111)	(0.293)	(0.093)*	(0.258)**
Observations	618	618	642	642	586	586	617	617	586	574	617	610
R^2	0.125		0.119		0.073		0.068		0.101		0.081	
Sub-district FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Basic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors (clustered at the village level) are in parentheses. Reported estimates are coefficients from OLS and tobit regressions and marginal effects for probit regressions. Tobit reports the coefficients for the latent regression model. Thus, the coefficients can be interpreted just as coefficients from OLS. Basic controls include respondent's gender, age, education, marital, health and household head status, subjective wealth, risk preferences, pre-prime time preferences and household size. */**/*** denotes significant at the 10/5/1 percent significance levels.

Table 7: The Impact of Priming: Recent Disability (Disability sample)

	IDF1		IDF2		Beta1		Beta2		Pb1		Pb2	
	OLS	Tobit	OLS	Tobit	OLS	Tobit	OLS	Tobit	OLS	Probit	OLS	Probit
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Recent disability	-0.083	-0.139	-0.012	-0.008	0.261	0.261	0.005	-0.000	-0.177	-0.506	0.028	0.105
	(0.066)	(0.078)*	(0.069)	(0.110)	(0.119)**	(0.107)**	(0.089)	(0.091)	(0.132)	(0.361)	(0.103)	(0.290)
NP	-0.046	-0.076	-0.035	-0.056	0.324	0.324	0.247	0.270	-0.264	-0.763	-0.009	0.014
	(0.064)	(0.082)	(0.060)	(0.094)	(0.121)***	(0.109)***	(0.158)	(0.154)*	(0.110)**	(0.311)**	(0.110)	(0.310)
PP	-0.025	-0.041	-0.028	-0.039	0.248	0.248	0.244	0.256	-0.178	-0.517	-0.080	-0.247
	(0.063)	(0.082)	(0.066)	(0.097)	(0.148)*	(0.134)*	(0.177)	(0.169)	(0.124)	(0.331)	(0.117)	(0.324)
Recent disability x PP	0.049	0.089	-0.011	-0.021	-0.257	-0.257	-0.122	-0.111	0.214	0.595	-0.061	-0.228
	(0.088)	(0.110)	(0.093)	(0.140)	(0.205)	(0.184)	(0.217)	(0.208)	(0.174)	(0.468)	(0.159)	(0.465)
Recent disability x NP	0.161	0.232	0.153	0.232	-0.592	-0.592	-0.207	-0.251	0.505	1.433	-0.034	-0.155
	(0.091)*	(0.114)**	(0.081)*	(0.123)*	(0.177)***	(0.160)***	(0.165)	(0.170)	(0.177)***	(0.485)***	(0.166)	(0.448)
Observations	271	271	279	279	256	256	265	265	256	241	265	256
R^2	0.204		0.189		0.198		0.170		0.208		0.195	
Sub-district FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Basic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Rgeressions are based on the disability sample only. Standard errors (clustered at the sub-district level) are in parentheses. Reported estimates are coefficients from OLS and tobit regressions and marginal effects for the probit regressions. Basic controls include respondent's gender, age, education, marital, health and household head status, subjective wealth, risk preferences, pre-prime time preferences and household size. */**/*** denotes significant at the 10/5/1 percent significance levels.

Table 8: The Impact of Priming: Recent Disability

	IDF1		IDF2		Beta1		Beta2		Pb1		Pb2	
	OLS	Tobit	OLS	Tobit	OLS	Tobit	OLS	Tobit	OLS	Probit	OLS	Probit
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Recent disability	-0.011	-0.028	0.044	0.079	0.038	0.038	-0.197	-0.217	0.003	0.009	0.115	0.329
	(0.051)	(0.060)	(0.052)	(0.090)	(0.082)	(0.078)	(0.089)**	(0.095)**	(0.107)	(0.279)	(0.077)	(0.206)
NP	0.010	0.015	-0.000	-0.003	0.036	0.036	0.039	0.042	-0.014	-0.053	0.068	0.203
	(0.033)	(0.043)	(0.032)	(0.061)	(0.045)	(0.043)	(0.077)	(0.078)	(0.059)	(0.162)	(0.049)	(0.139)
PP	0.019	0.029	0.037	0.067	0.028	0.028	0.001	-0.008	0.024	0.070	0.045	0.145
	(0.032)	(0.041)	(0.032)	(0.054)	(0.062)	(0.059)	(0.078)	(0.079)	(0.063)	(0.169)	(0.050)	(0.141)
Recent disability x PP	0.025	0.040	-0.053	-0.086	-0.041	-0.041	0.107	0.131	0.044	0.110	-0.166	-0.501
	(0.065)	(0.080)	(0.073)	(0.120)	(0.139)	(0.133)	(0.123)	(0.128)	(0.140)	(0.367)	(0.117)	(0.328)
Recent disability x NP	0.101	0.138	0.117	0.196	-0.263	-0.263	-0.026	-0.047	0.231	0.619	-0.068	-0.193
	(0.066)	(0.084)	(0.068)*	(0.112)*	(0.111)**	(0.107)**	(0.139)	(0.151)	(0.135)*	(0.355)*	(0.135)	(0.349)
Observations	618	618	642	642	586	586	617	617	586	574	617	610
R^2	0.117		0.118		0.078		0.068		0.104		0.080	
Sub-district FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Basic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors (clustered at the sub-district level) are in parentheses. Reported estimates are coefficients from OLS and tobit regressions and marginal effects for the probit regressions. Basic controls include respondent's gender, age, education, marital, health and household head status, subjective wealth, risk preferences, pre-prime time preferences and household size. */**/*** denotes significant at the 10/5/1 percent significance levels.

In order to see if there is a temporary shift in time preferences after the disability event in the household, Table 7 (Table 8) shows the results for regressions for the disability sample including an indicator variable if the disability shock was recent (less than eight years ago) and an interaction of this indicator with *PP* and *NP*. The coefficient of *Recent disability* is statistically significant in the Tobit regression on *IDF1*, and in both regressions on *Beta1*. Thus, respondents that live in a household where a recent disability shock occurred, are on average less patient and less present biased for a delay of five weeks compared to households where the disability shock occurred more than eight years ago. The interaction term for recent disability and negative prime is statistically significant in all regression except for *Beta2* and *Pb2*. Thus, the negative prime has a significant treatment effect for respondents that live in a disability household where the disability occurred recently. On average, respondents that live in a recent disability household and received a negative prime are significantly more patient (both delays), more present biased and more likely to be present bias for a delay of five weeks. The effect is sizable. For example, a respondent that lives in a recent disability household and received the negative prime has on average a 0.16 unites larger *IDF1* and a 0.59 units smaller *Beta1* than respondents that live in no-recent disability households and received the negative prime. Finally, Table 9 shows the results for regressing *Patience scale* on the binary variables for life satisfaction and subjective wellbeing. The positive and statistically significant coefficients for *Patience scale* show that there is a positive association between patience and wellbeing. This supports the argument that different time preferences across disability and non-disability households could be one channel through which household disability affects poverty.

4.1 Robustness Checks

This section presents the results for a number of robustness checks starting with a series of regressions that add additional control variables to the main regressions. First of all, we test if the results are robust to the inclusion of the other pre-prime time preference measure. Table A.1 shows the regression results for using *Patience scale* instead of *Patient decision*. Generally, the results remain unchanged. The treatment effect of the positive prime for *IDF2* becomes statistically significant at the five percent level.

Since personality traits could be a relevant determinant affecting an individuals time preference we add some personality traits as control variables. Table A.2 shows the results for the main regressions with additional controls for the Big Five personality traits. Overall, the results are robust to the inclusion of the personality characteristics. However, the treatment effect of the positive primes becomes insignificant for *Pb2* in the OLS specification. Thus, some differences in personality characteristics may explain the previously measured significant treatment effect. For *Pb2* this might be the openness trait since its coefficient is highly statistically significant. Having a higher score in

Table 9: General Relationship between Patience and Wellbeing Outcomes

	Life satisfaction		Wellbeing	
	OLS	Probit	OLS	Probit
	(1)	(2)	(3)	(4)
Patience scale	0.013	0.040	0.014	0.043
	(0.007)*	(0.020)**	(0.006)**	(0.019)**
Constant	-0.670	-2.536	-0.325	-3.103
	(0.274)**	(1.172)**	(0.265)	(0.815)***
Observations	613	608	613	608
R^2	0.104		0.237	
Sub-district FE	Yes	Yes	Yes	Yes
Basic controls	Yes	Yes	Yes	Yes

Notes: Standard errors (clustered at the village level) are in parentheses. Reported estimates are coefficients from OLS regressions and marginal effects for probit regressions. Life satisfaction is equal to one if the respondent is completely satisfied or very satisfied with his or her life as a whole. Subject wellbeing is equal to one if the respondent perceives his- or herself to be between the third and sixth step of a six-step ladder, where on the bottom stand the poorest person of the village, and on the highest step, stand the richest people of the village. Basic controls include respondent's gender, age, education, marital, health and household head status, subjective wealth, risk preferences, and household size. */**/*** denotes significant at the 10/5/1 percent significance levels.

Openness to experience decreases the likelihood to be present biased for a delay of nine weeks. The coefficient for *Openness to experience* is also highly statistically significant for *IDF2*. While the coefficient for *Extraversion* is statistically significant in the regressions on *IDF1*, *Beta1* and *Pb1*, the coefficient for *Agreeableness* is only statistically significant in the regression on *Pb1*. The coefficients for *Conscientiousness* and *Neuroticism* are not statistically significant in any of the regressions. The results suggest that *Openness to experience* is more important for a longer delay and *Extraversion* as well as *Agreeableness* for a shorter delay. Interestingly, none of the personality variables are statistically significant in the regressions for *Beta2* for which the treatment effect of the positive prime remains statistically significant.

Typical concerns of cross-sectional studies are selective migration patterns which could bias the results. The reason is that respondents' migration pattern could be correlated with households' disability status as well as with the respondents' time preferences (Goldbach and Schlüter 2018). Therefore, Table A.3 shows the results for the inclusion of a continuous variable measuring the years since the respondent lives in the study village. Results remain largely unchanged.

In order to rule out that the results are driven by district characteristics, we include district instead of sub-district fixed effects. Using district fixed effects turns the treatment effect of the positive prime insignificant in the OLS specification for the outcome

Pb2 and in the regression on *IDF2*. However, the treatment effect for *Beta2* remains significant. In addition, to rule out that the results depend on the level of standard error clustering, we consider a higher and thus, more conservative level of clustered standard errors.[14] The treatment effect for the positive primes remains robust for *Beta2*. The coefficient in the OLS specification is statistically significant at the five percent significance level. However, the treatment effect of the positive prime for *Pb2* remains statistically significant at the ten percent level in the probit specification.

The sample includes respondents with implausibly high values for *Beta1* and *Beta2*. It is conceivable that some respondents exhibit future bias rather than present bias, which would indicate a value for *Beta1* and *Beta2* greater than one. However, it might be that many of the very highest values also reflect noise. Therefore, Table A.4 reports the results for re-running the main regressions but excluding the observations with values for *Beta1* and *Beta2* above the 95th percentile which is 1.4 for both variables. After dropping these respondents, 2.48 percent and 3.38 percent are future biased for a delay of five and nine weeks, respectively. While the treatment effect of the positive prime on *IDF2* is only statistically significant at the ten percent level in the tobit specification, the treatment effect for the outcome *Beta2* even becomes statistically significant at the one percent significance level.

We further more, split the sample by gender and age. Tables A.5 and A.6 show the results for the female and male sub-sample, respectively we did the same regressions for age.[15] Interestingly, the statistically significant coefficients for the disability sample remain robust for the female and the above median age sub-sample. The treatment effect of the positive prime on *Beta2* and *Pb2* only remain significant for the male and above-median age sub-sample. For the below median age sub-sample, the difference in patience and present bias between the disability and non-disability sample decreases and becomes insignificant in most specifications. In addition, the treatment effects turn insignificant. These sample split reveals that the female and older respondents seem to drive the difference in time preferences between the disability and non-disability sample. In addition, male and above median age respondents drive the treatment effect for the positive prime on the outcomes *IDF2*, *Beta2* and *Pb2*.

Moreover we estimate the regressions separately for the disability sample and the non-disability sample. Regressing the primes on the outcome variables for the non-disability sample constitutes a placebo regression since the primes were not meant to affect the outcomes in the non-disability sample. On the one hand, the regressions confirm the previous results. The positive and (in one regression) negative primes had a significant effect on *Beta2* for the disability sample. However, the primes also significantly affected

[14] The number of districts does not allow clustering at an even higher level, i.e. at the district level, since the number of independent observations would be too small.

[15] Regressions for the age sub-sample can be obtained upon request.

IDF2 and *Pb2* in the non-disability sample.[16]

5 Discussion

This section aims to link the different findings together, interpret results in the context of the theoretical and empirical literature, examine channels and possible reasons for the obtained results as well as implications for research and policy-making.

The empirical analysis suggests that there is a temporary effect of the disability environment on individual time preferences. The results suggest that respondents who live in households where a household member acquired recently a disability seem to be more patient and more present biased. While these findings reject the first research hypothesis, they cannot reject the research hypothesis II.[17] Contrary to the theoretical considerations in the introduction of this paper, the recent disability shock seems to make respondents more patient. Following the rational from Bjorklund and Kipp (1996) who suggest that females are more patient than males due to the need to delay their own gratification for their children's needs, household members of PWDs could be more patient because they need to care for and assist the disabled household member. Since these care-giving activities require them to put their own needs aside, they might adapt to delay gratification making them more patient if they are not offered and immediate option. However, following the outline of the second research hypothesis, deferring available immediate gratification might be more difficult for them compared to household members of non-disability households. This is likely to be the result of a number of factors. The need to care for the disabled household member and organize an inclusive daily life for them is likely to cause stress and a high level of mental load. As a result, they might have greater mental burden and thus might be less able to imagine the future, or lower willpower to resist the available immediate gratification which might make them more present biased. Slonim et al. (2007) refer to the mental costs of recalling, such as recalling that there was a payment from the experiment and to check if they have received the payment, as remembering costs. Household members of disability households might not have the capacity to bear this additional costs which makes it more convenient to take the immediate reward.

An additional channel could be emotional regulation. Research from psychology suggests that individuals with less well regulated emotions are more likely to choose the immediate reward and engage in impulsive behaviors in order to reduce negative emotions (Lin and Epstein 2014; Malesza 2019; Schreiber et al. 2012). Since it is conceivable

[16] Results can be obtained upon request.

[17] The hypotheses were: *Hypothesis I:* Individuals that live in disability households discount the future more heavily than individuals that live in non-disability households. *Hypothesis II:* Individuals that live in disability households are more present biased than individuals that live in non-disability households.

that a disability shock in the household triggers a number of emotions, it might be that these less well regulated emotions affect the household members' intertemporal decisions.
The reason for the temporary effect may be that household members adapt to the new situation maybe through reorganizing the daily routine and receiving help from other family members outside the household. In addition, household members may better regulate their emotions some years after the disability shock. However, since priming prompts people to remember past disability-related thoughts, actions and feelings, it seems reasonable to find an effect only for recent disability shocks. Disability-related thoughts, actions and feelings are arguably stronger and more present in case of a recent disability event.
Whereas the negative primes were designed to activate disability-related mental representations, the positive primes were designed to control if the response to primes is generally driven by emotions. The treatment effect of the positive primes on individual time preferences is evidence that emotions generally affect the intertemporal decision-making process. Overall, positive primes make the whole sample more patient and the disability sample less present biased. This is in line with previous research on emotions and decision-making (Loewenstein 1996; Loewenstein and Lerner 2003). Positive emotions are argued to make individuals more optimistic which has a direct and and indirect effect on their intertemporal decisions (Loewenstein and Lerner 2003; Daly et al. 2009). For example, Ifcher and Zarghamee (2011) find that inducing positive stimuli, significantly reduces the required rate of return. For the disability sample, it is conceivable that the positive primes reduced the relative weight of the disability environment. As a result, respondents of the disability sample that received the positive primes have a lower likelihood to be present biased.
At first glance, it seems surprising that the effect of the negative and positive primes go in the same direction. However, it is in line with empirical research related to emotions and time preferences. For example, Melrose (2015) find that happy and fearful face primes increased impulsive choices. In contrast, Drichoutis and Nayga (2013) find that negative and positive mood states affect time preferences by increasing patience. Finally, McLeish and Oxoby (2007) find a mood effect on time preferences only for women.
Whether the priming effects operate through the proposed channels cannot be tested and should be addressed in future research. A fruitful avenue would be to try to more sharply disentangle these aspects, perhaps by designing a set of disability-related primes each aiming to activate a different dimension of concerns.
The two-system models of individual decision making seems to be a helpful way to think about the psychological impacts of household disability. The model describes the decision-making process as a result of a strategic interplay between an impulsive and a

forward-looking agent (Bernheim and Rangel 2004; Fudenberg and Levine 2006). The forward-looking agent can reduce the influence of the impulsive agent only by drawing on limited cognitive resources. Thus, household members of disability households might not fundamentally have different time preferences but their impulsive self may more easily affect behavior due to an increased mental load and stress associated with household disability.

A concern about the identification strategy is that the negative primes were found to have a significant effect in the split sample regressions for the non-disability sample. One potential reason for this effect might be that the negative primes did not only activate mental representations that are associated with disability but with poor health conditions more generally. Non-disability households might include members with poor health conditions that are not disabled or are not identified as having a disability but whose impairments are similar to the impairments caused by a disability. This underlines the difficulty of identifying and studying disability. Disability is complex and very heterogeneous meaning that there are many different types of disabilities, e.g. a disability can be physical, cognitive, psychosocial, communicative, or sensory, with varying degrees of severity. The resulting impairments are even more heterogeneous since they depend on the institutional, social and physical environment.

Since the estimated effects only measure the effect of the activated or intensified mental representations on time preference, the true underlying effect of disability on individual time preferences is likely to be larger. This argument is supported by the fact that the primes were not directly administered before the time preference games and priming effects are known to decrease over time (Higgins et al. 1985). As a result, priming seems to be useful tool to uncover qualitative effects but it is less informative about the magnitude of the impact of household disability on time preferences.

All in all, our results provide new information for public policies dealing with disability households and their behaviours. They furthermore show that patience, as a character trait and a present bias, as an individual preference, are not stable, and shift when a disability shock in the household occurs, especially in a already vulnerable household.

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Appendix

Table A.1: The Impact of Priming: Different Control for Pre-prime Time Preferences

	IDF1		IDF2		Beta1		Beta2		Pb1		Pb2	
	OLS	Tobit	OLS	Tobit	OLS	Tobit	OLS	Tobit	OLS	Probit	OLS	Probit
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
DS	0.068	0.090	0.100	0.177	-0.114	-0.114	-0.218	-0.233	0.120	0.333	0.092	0.271
	(0.037)*	(0.046)*	(0.041)**	(0.074)**	(0.061)*	(0.059)*	(0.084)**	(0.088)***	(0.073)	(0.193)*	(0.069)	(0.191)
NP	0.021	0.036	0.019	0.036	-0.041	-0.041	-0.030	-0.031	0.042	0.110	0.102	0.301
	(0.036)	(0.045)	(0.039)	(0.077)	(0.049)	(0.047)	(0.086)	(0.087)	(0.066)	(0.183)	(0.058)*	(0.161)*
Disability sample x NP	0.005	-0.005	-0.018	-0.033	0.079	0.079	0.165	0.172	-0.050	-0.132	-0.121	-0.349
	(0.052)	(0.064)	(0.057)	(0.102)	(0.087)	(0.083)	(0.132)	(0.134)	(0.093)	(0.248)	(0.099)	(0.270)
PP	0.030	0.045	0.072	0.131	-0.027	-0.027	-0.073	-0.089	0.077	0.216	0.090	0.275
	(0.039)	(0.048)	(0.037)*	(0.066)**	(0.069)	(0.066)	(0.083)	(0.085)	(0.074)	(0.198)	(0.059)	(0.168)
Disability sample x PP	-0.019	-0.021	-0.110	-0.186	0.107	0.107	0.229	0.253	-0.104	-0.292	-0.176	-0.518
	(0.054)	(0.068)	(0.054)**	(0.094)**	(0.109)	(0.104)	(0.123)*	(0.126)**	(0.111)	(0.290)	(0.093)*	(0.257)**
Observations	618	618	642	642	586	586	617	617	586	574	617	610
R^2	0.095		0.080		0.074		0.068		0.089		0.076	
Sub-district FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Basic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors (clustered at the village level) are in parentheses. Reported estimates are coefficients from OLS and tobit regressions and marginal effects for the probit regressions. Basic controls include respondent's gender, age, education, marital, health and household head status, subjective wealth, risk preferences, pre-prime time preferences and household size. The difference to the main regressions is that pre-prime time preferences are measured using *Patience scale* instead of *Patient decision*. */**/*** denotes significant at the 10/5/1 percent significance levels.

Table A.2: The Impact of Priming: Additional Controls

	IDF1		IDF2		Beta1		Beta2		Pb1		Pb2	
	OLS	Tobit	OLS	Tobit	OLS	Tobit	OLS	Tobit	OLS	Probit	OLS	Probit
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
DS	0.071	0.095	0.096	0.171	-0.131	-0.131	-0.220	-0.237	0.109	0.326	0.081	0.261
	(0.039)*	(0.048)**	(0.042)**	(0.074)**	(0.061)**	(0.058)**	(0.091)**	(0.094)**	(0.072)	(0.196)*	(0.070)	(0.197)
NP	0.020	0.034	0.021	0.040	-0.050	-0.050	-0.037	-0.039	0.041	0.115	0.102	0.321
	(0.036)	(0.044)	(0.040)	(0.076)	(0.049)	(0.047)	(0.087)	(0.087)	(0.066)	(0.185)	(0.058)*	(0.164)*
Disability sample x NP	0.008	-0.001	-0.009	-0.017	0.094	0.094	0.174	0.180	-0.034	-0.105	-0.104	-0.307
	(0.053)	(0.065)	(0.058)	(0.103)	(0.088)	(0.084)	(0.129)	(0.131)	(0.095)	(0.256)	(0.102)	(0.278)
PP	0.020	0.033	0.060	0.110	-0.040	-0.040	-0.079	-0.095	0.071	0.215	0.069	0.232
	(0.037)	(0.046)	(0.035)*	(0.062)*	(0.066)	(0.063)	(0.087)	(0.088)	(0.072)	(0.198)	(0.061)	(0.175)
Disability sample x PP	-0.002	-0.001	-0.091	-0.156	0.123	0.123	0.234	0.259	-0.079	-0.240	-0.148	-0.466
	(0.054)	(0.067)	(0.054)*	(0.093)*	(0.111)	(0.105)	(0.129)*	(0.131)**	(0.109)	(0.291)	(0.096)	(0.267)*
Conscientiousness	-0.006	-0.011	0.004	0.009	0.016	0.016	-0.002	-0.002	0.007	0.020	0.017	0.047
	(0.009)	(0.012)	(0.009)	(0.016)	(0.016)	(0.015)	(0.030)	(0.029)	(0.017)	(0.044)	(0.015)	(0.042)
Open to experience	-0.008	-0.008	-0.014	-0.029	-0.011	-0.011	-0.001	-0.003	-0.004	-0.013	-0.028	-0.084
	(0.006)	(0.007)	(0.005)**	(0.010)***	(0.010)	(0.010)	(0.015)	(0.015)	(0.010)	(0.028)	(0.010)***	(0.029)***
Extraversion	-0.011	-0.019	-0.003	-0.003	0.031	0.031	0.012	0.011	-0.035	-0.101	0.001	0.002
	(0.008)	(0.010)*	(0.009)	(0.016)	(0.015)**	(0.014)**	(0.021)	(0.021)	(0.016)**	(0.042)**	(0.016)	(0.044)
Agreeableness	0.006	0.010	0.004	0.009	-0.009	-0.009	0.014	0.012	0.025	0.069	0.014	0.044
	(0.006)	(0.008)	(0.007)	(0.012)	(0.013)	(0.012)	(0.017)	(0.017)	(0.012)**	(0.031)**	(0.012)	(0.034)
Neuroticism	-0.007	-0.006	-0.007	-0.018	-0.018	-0.018	-0.001	-0.002	-0.007	-0.019	0.000	-0.002
	(0.007)	(0.008)	(0.006)	(0.011)	(0.012)	(0.011)	(0.015)	(0.014)	(0.012)	(0.031)	(0.011)	(0.032)
Observations	617	617	641	641	585	585	616	616	585	573	616	609
R^2	0.135		0.129		0.088		0.070		0.114		0.097	
Sub-district FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Basic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Additional controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors (clustered at the village level) are in parentheses. Reported estimates are coefficients from OLS and tobit regressions or marginal effects for the probit regressions. Basic controls include respondent's gender, age, education, marital, health and household head status, subjective wealth, risk preferences, pre-prime time preferences and household size. Additional controls include the Big Five personality characteristics. */**/*** denotes significant at the 10/5/1 percent significance levels.

Table A.3: The Impact of Priming: Control for Migration to the Village

	IDF1		IDF2		Beta1		Beta2		Pb1		Pb2	
	OLS	Tobit	OLS	Tobit	OLS	Tobit	OLS	Tobit	OLS	Probit	OLS	Probit
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
DS	0.074	0.096	0.105	0.192	-0.128	-0.128	-0.226	-0.242	0.122	0.350	0.106	0.320
	(0.039)*	(0.049)*	(0.041)**	(0.074)***	(0.060)**	(0.057)**	(0.086)***	(0.090)***	(0.073)*	(0.196)*	(0.070)	(0.195)
NP	0.025	0.039	0.024	0.049	-0.047	-0.047	-0.032	-0.034	0.043	0.116	0.108	0.326
	(0.035)	(0.043)	(0.038)	(0.074)	(0.049)	(0.047)	(0.084)	(0.085)	(0.067)	(0.186)	(0.056)*	(0.160)**
Disability sample x NP	0.003	-0.005	-0.020	-0.044	0.088	0.088	0.173	0.180	-0.047	-0.137	-0.129	-0.375
	(0.052)	(0.064)	(0.058)	(0.102)	(0.085)	(0.081)	(0.130)	(0.133)	(0.094)	(0.252)	(0.101)	(0.275)
PP	0.026	0.039	0.071	0.133	-0.033	-0.033	-0.076	-0.091	0.073	0.211	0.090	0.283
	(0.037)	(0.047)	(0.034)**	(0.061)**	(0.065)	(0.062)	(0.084)	(0.085)	(0.073)	(0.198)	(0.059)	(0.167)*
Disability sample x PP	-0.010	-0.010	-0.103	-0.181	0.108	0.108	0.229	0.253	-0.092	-0.264	-0.170	-0.515
	(0.054)	(0.069)	(0.054)*	(0.093)*	(0.108)	(0.103)	(0.123)*	(0.127)**	(0.111)	(0.293)	(0.093)*	(0.258)**
Observations	618	618	642	642	586	586	617	617	586	574	617	610
R^2	0.125		0.120		0.079		0.069		0.101		0.084	
Sub-district FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Basic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors (clustered at the village level) are in parentheses. Reported estimates are coefficients from OLS and tobit regressions or marginal effects for the probit regressions. Basic controls include respondent's gender, age, education, marital, health and household head status, subjective wealth, risk preferences, pre-prime time preferences and household size. Regression additionally includes a continuous variable capturing the years since the respondent lives in the study village. */**/*** denotes significant at the 10/5/1 percent significance levels.

Table A.4: The Impact of Priming: Excluding Outliers

	IDF1		IDF2		Beta1		Beta2		Pb1		Pb2	
	OLS	Tobit	OLS	Tobit	OLS	Tobit	OLS	Tobit	OLS	Probit	OLS	Probit
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
DS	0.058	0.078	0.078	0.139	-0.048	-0.048	-0.077	-0.084	0.095	0.276	0.056	0.185
	(0.042)	(0.052)	(0.043)*	(0.075)*	(0.051)	(0.049)	(0.048)	(0.049)*	(0.077)	(0.207)	(0.072)	(0.199)
NP	0.016	0.031	0.018	0.042	-0.023	-0.023	-0.064	-0.065	0.033	0.095	0.109	0.331
	(0.037)	(0.046)	(0.041)	(0.077)	(0.048)	(0.046)	(0.039)	(0.039)*	(0.070)	(0.194)	(0.060)*	(0.170)*
Disability sample x NP	0.009	-0.004	0.002	0.000	0.029	0.029	0.093	0.095	-0.032	-0.096	-0.087	-0.268
	(0.056)	(0.070)	(0.061)	(0.105)	(0.069)	(0.066)	(0.070)	(0.071)	(0.097)	(0.258)	(0.105)	(0.282)
PP	0.023	0.037	0.074	0.148	-0.033	-0.033	-0.110	-0.116	0.088	0.262	0.117	0.363
	(0.038)	(0.049)	(0.038)*	(0.067)**	(0.052)	(0.049)	(0.044)**	(0.045)**	(0.073)	(0.197)	(0.063)*	(0.176)**
Disability sample x PP	0.008	0.013	-0.091	-0.164	0.034	0.034	0.188	0.198	-0.087	-0.255	-0.166	-0.513
	(0.057)	(0.074)	(0.058)	(0.098)*	(0.074)	(0.071)	(0.068)***	(0.069)***	(0.112)	(0.298)	(0.095)*	(0.261)**
Observations	576	576	595	595	546	546	570	570	546	533	570	561
R^2	0.138		0.125		0.095		0.099		0.119		0.096	
Sub-district FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Basic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors (clustered at the sub-district level) are in parentheses. Reported estimates are coefficients from OLS and tobit regressions and marginal effects for the probit regressions. Basic controls include respondent's gender, age, education, marital, health and household head status, subjective wealth, risk preferences, pre-prime time preferences and household size. */**/*** denotes significant at the 10/5/1 percent significance levels.

Table A.5: The Impact of Priming: Female Respondents

	IDF1		IDF2		Beta1		Beta2		Pb1		Pb2	
	OLS	Tobit	OLS	Tobit	OLS	Tobit	OLS	Tobit	OLS	Probit	OLS	Probit
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
DS	0.099	0.142	0.110	0.181	-0.127	-0.127	-0.194	-0.205	0.207	0.631	0.095	0.315
	(0.053)*	(0.065)**	(0.047)**	(0.082)**	(0.081)	(0.075)*	(0.171)	(0.166)	(0.081)**	(0.234)***	(0.085)	(0.251)
NP	0.039	0.065	0.021	0.043	-0.065	-0.065	0.026	0.021	0.114	0.360	0.161	0.521
	(0.050)	(0.057)	(0.047)	(0.088)	(0.094)	(0.087)	(0.152)	(0.145)	(0.084)	(0.237)	(0.086)*	(0.246)**
Disability sample x NP	-0.024	-0.054	0.031	0.035	0.189	0.189	0.006	-0.008	-0.170	-0.537	-0.129	-0.420
	(0.066)	(0.078)	(0.066)	(0.114)	(0.139)	(0.129)	(0.181)	(0.178)	(0.105)	(0.274)*	(0.154)	(0.425)
PP	0.016	0.040	0.058	0.095	0.030	0.030	-0.033	-0.048	0.057	0.185	0.086	0.302
	(0.045)	(0.054)	(0.042)	(0.073)	(0.091)	(0.085)	(0.137)	(0.133)	(0.087)	(0.256)	(0.075)	(0.226)
Disability sample x PP	-0.015	-0.028	-0.038	-0.052	0.151	0.151	0.163	0.173	-0.145	-0.438	-0.089	-0.303
	(0.059)	(0.073)	(0.058)	(0.095)	(0.149)	(0.138)	(0.196)	(0.194)	(0.115)	(0.326)	(0.121)	(0.339)
Observations	370	370	389	389	352	352	371	371	352	333	371	362
R^2	0.185		0.214		0.142		0.101		0.181		0.143	
Sub-district FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Basic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors (clustered at the sub-district level) are in parentheses. Reported estimates are coefficients from OLS and tobit regressions and marginal effects for the probit regressions. Basic controls include respondent's gender, age, education, marital, health and household head status, subjective wealth, risk preferences, pre-prime time preferences and household size. */**/*** denotes significant at the 10/5/1 percent significance levels.

Table A.6: The Impact of Priming: Male Respondents

	IDF1		IDF2		Beta1		Beta2		Pb1		Pb2	
	OLS	Tobit	OLS	Tobit	OLS	Tobit	OLS	Tobit	OLS	Probit	OLS	Probit
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
DS	0.029	0.031	0.093	0.175	0.019	0.019	-0.180	-0.202	-0.073	-0.204	0.071	0.204
	(0.069)	(0.076)	(0.079)	(0.134)	(0.112)	(0.100)	(0.095)*	(0.097)**	(0.130)	(0.384)	(0.119)	(0.343)
NP	-0.020	-0.024	-0.009	-0.005	0.008	0.008	-0.082	-0.083	-0.063	-0.274	0.005	0.011
	(0.061)	(0.071)	(0.068)	(0.132)	(0.095)	(0.085)	(0.112)	(0.107)	(0.103)	(0.335)	(0.111)	(0.325)
Disability sample x NP	0.056	0.056	-0.000	-0.011	-0.035	-0.035	0.391	0.419	0.150	0.493	-0.083	-0.229
	(0.101)	(0.118)	(0.109)	(0.198)	(0.152)	(0.136)	(0.247)	(0.237)*	(0.188)	(0.578)	(0.182)	(0.525)
PP	0.053	0.058	0.080	0.151	-0.137	-0.137	-0.194	-0.221	0.132	0.393	0.134	0.385
	(0.064)	(0.073)	(0.064)	(0.112)	(0.090)	(0.080)*	(0.098)*	(0.097)**	(0.109)	(0.301)	(0.103)	(0.281)
Disability sample x PP	-0.009	0.001	-0.167	-0.308	0.027	0.027	0.280	0.327	0.017	0.062	-0.273	-0.815
	(0.099)	(0.112)	(0.110)	(0.193)	(0.144)	(0.129)	(0.124)**	(0.134)**	(0.181)	(0.505)	(0.157)*	(0.465)*
Observations	248	248	253	253	234	234	246	246	234	211	246	235
R^2	0.209		0.185		0.178		0.197		0.218		0.162	
Sub-district FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Basic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors (clustered at the sub-district level) are in parentheses. Reported estimates are coefficients from OLS and tobit regressions and marginal effects for the probit regressions. Basic controls include respondent's gender, age, education, marital, health and household head status, subjective wealth, risk preferences, pre-prime time preferences and household size. */**/*** denotes significant at the 10/5/1 percent significance levels.