ESSAYS ON ASSET MARKETS AND SELF-ASSESSED HEALTH STATUS

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This dissertation consists of three chapters on individual decision making in asset markets and subjective assessment of health status. The first chapter studies price convergence in asset markets with indefinite duration induced by existence of bankruptcy risk. By introducing increasing and decreasing fundamental value paths via experimental methodology, this chapter extends knowledge about traders' incentives in asset markets with indefinite horizons. In most cases, the data indicate significant undervaluation of assets without a buyback value under bankruptcy risk regardless of fundamental value regime. The transaction prices closely follow the fundamental value trend of the asset supported by a terminal value in both definite and indefinite time horizons with constant fundamentals. The second chapter uses cross country survey data from Turkey and the United States to analyze determinants of gender differences in self-assessed health status. Ordered logit models are estimated to quantify the effects of factors that prove important in self-rated health outcomes. While some findings on the relationship between socioeconomic status indicators and self-assessed health level match earlier results, significant gender gap remains even with controls for chronic illnesses. Hierarchical ordered probit estimation reveals that reporting thresholds are significantly affected by gender of the respondents in both countries. The last chapter explains the gender differences in self-assessed health status by providing a theoretical identification mechanism via dynamic model which allows for heterogeneity in discount factor of individuals. Theoretical implications are empirically tested and estimation results support the structural model implications. We conclude that accounting for heterogeneity in individual discount factors explains substantial portion of the gender gap in self-assessed health status.

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PREFACE

There are many people I would like to express my gratitude for their help on my way to get this accomplishment. I would like to thank my advisors John Duffy and Jean-François Richard for their guidance and inspiration throughout the formation of my dissertation. John guided and supported my work on the field of behavioral finance. I have learned a lot from him on conducting research in experimental economics. It was a great pleasure and chance to have Jean-François Richard as my advisor. His guidance had crucial role at different stages of my dissertation. I appreciate his guidance and insight for my work on the field of health economics and application of econometric methods. I also thank the committee members, Gunduz Caginalp, Werner Troesken and Stephanie Wang for devoting their time and providing helpful comments and discussions. I have special thanks to Mehmet Soytas who was my co-author in two chapters of this dissertation. I have greatly benefited from my research collaboration with him. Additionally, I would like to thank many others who helped me in different ways and they are Alistair Wilson, Sera Linardi, Paul Noroski, Andreas Blume, Sourav Bhattacharya, Marla Ripoll and Juergen Huber. I am in particular grateful to Thomas Rawski and Jeesoo Sohn for reading and editing my papers. I would like to express my deep gratitude to Aylin Ege who encouraged me to pursue an academic career. Without her continuous support during my previous academic studies in Ankara, I could not make it this far. Finally, I thank my parents and friends for their support.

1.0 PRICE CONVERGENCE AND FUNDAMENTALS IN ASSET MARKETS WITH BANKRUPTCY RISK: AN EXPERIMENT

1.1 INTRODUCTION

Asset market efficiency draws remarkable attention in economics and finance. History has borne witness to dramatic welfare losses of societies due to extensive price fluctuations within many markets: e.g. the Dutch "tulipmania" of 1630s or the stock market crash of the Great Depression. The significant changes to the NASDAQ share index in the early 2000s are just a recent example of a bubble and crash which refers to a period of rapidly increasing prices with a sudden decline towards the end (Dufwenberg et al. (2005)(37)). The latest world-wide financial crisis of 2008 is also associated with a bubble in mortgage backed securities and stock market crashes, which led to huge welfare losses for the world economy. Mispricing of financial assets, especially securities backed by mortgage system, is widely considered to be the initial cause of the recession[1]. Thus, asset market efficiency is again proven to be a crucial area of concern not only for economists, but also for public policy makers.

Asset market decisions are associated with uncertainties for economic agents, especially during economic downturns. For instance, many firms including Lehman Brothers filed for bankruptcy during the U.S. mortgage crisis of 2008[2]. Moreover, sovereign debt problems of many countries increase the probability of government defaults and debt rescheduling, even moratorium or repudiation in extreme cases. During the moratorium of 2001, Argentina

[1] See Acharya and Richardson (2009)(1) for a discussion.

[2] According to the OECD (2012)(93), number of firms filing for bankruptcy significantly increased in the United States and Europe in 2009. OECD Index for number of bankruptcies is 312 for U.S. in the third quarter of 2009 whereas the base year (2006) index is 100. For France and United Kingdom, the corresponding index is 124 and 138, respectively, during the second quarter of 2009.

bonds were priced at 25% of their face value (The Economist (2002)(114)). Recently, in April 2010, Greek government bonds were classified at junk bond level due to concerns over country default. The risks of default (bankruptcy) induce an indefiniteness on the lifetime and market values of stocks and government securities. Thus, investors often need to make decisions given the stochastic nature of asset markets where they run the risk of ending up with junk assets. Although the indefinite nature of decision making in asset markets is frequently observed, previous research mainly focuses on other aspects of markets to explain bubbles and crashes.

In an effort to understand the phenomenon of bubble and crash, my study analyzes markets for assets with bankruptcy risk. In these markets, referred to as asset markets with an indefinite duration, all assets have a common and fixed probability of becoming worthless after every trading period[3]. The questions proposed: Do asset markets with indefinite duration exhibit different outcomes than fixed horizon markets? Do prices converge to fundamental values for indefinitely lived assets? Do different fundamental value trends affect outcomes in asset markets with bankruptcy risk? The study takes advantage of experimental tools to set up asset markets with bankruptcy risk in order to analyze the effect of different fundamental value trends on pricing and efficiency.

Previous asset market experiments tested the efficient market hypothesis and mainly pointed out that trading prices significantly deviate from known fundamentals. Most experimental results are observed in an asset market with a declining fundamental value in a finite horizon (Smith et al. (1988)(108); King et al. (1993)(72)). Overpricing of an asset with decreasing fundamental value during middle periods of a fixed horizon market and an end-of-game market crash are robustly replicated findings. Experiments on constant fundamental value and finitely lived assets provided mixed results. Having different designs, some indicated price bubbles for flat fundamental value assets (Caginalp et al. (1998)(16); Noussair et al. (2001)(92); Bostian et al. (2006)(12)), whereas others reported price convergence (Kirchler et al. (2012)(74); Huber et al. (2012)(62)). Two studies considered an asset with increasing fundamentals and found persistent undervaluation of the asset in a fixed horizon

[3]If bankruptcy outcome is observed, then all assets are destroyed and the market closes. Asset life time and market duration have identical probability distribution. Thus, I use terms "indefinitely lived asset markets," "asset market with indefinite duration" and "asset market with bankruptcy risk" interchangeably.

market (Davies (2006)(33); Huber et al. (2012)(62)). On the other hand, Caginalp et al. (2002)(17) and Giusti et al. (2012)(49) reported price convergence for an increasing fundamental value asset under certain conditions. Very few papers have investigated experiments on assets with bankruptcy risk (Camerer and Weigelt (1993)(18); Ball and Holt (1998)(6); Hens and Steude (2009)(60)). All of them considered only a flat fundamental value for the asset and they reported mixed results due to differences in their experimental designs. Hens and Steude (2009)(60) observed undervaluation of the asset in treatments with fewer numbers of participants and price bubbles with larger number of traders. Camerer and Weigelt (1993)(18) indicated price convergence from below in some sessions as well as price bubbles for others, which have different number of traders and subject pool. Finally, Ball and Holt (1998)(6) ran a classroom experiment in which participants traded an indefinitely lived asset with a fixed dividend and a buy back value if the asset survived a ten period market game. Trading decisions were made by groups in this experiment. The authors did not employ any other comparable treatments and reported price bubbles for an asset with terminal value[4].

This study first aims to identify the effects of different fundamental value regimes on price convergence for indefinitely lived assets by using a comparable set up induced only by changes in a dividend process. Second, this study focuses on constant fundamental values with and without a terminal value, and then introducing increasing and decreasing fundamental value trends for indefinitely lived assets. Finally, the study provides a direct comparison between a fixed horizon asset market and an indefinitely lived asset market with constant fundamentals. I closely follow the recent literature and introduce a bankruptcy risk into design of Kirchler et al. (2012)(74), which used an asset with zero expected dividends and a terminal value. In the baseline treatment, the life-time of all assets and thus, the market duration are determined by a die roll. Therefore, the dividend process and the information structure are significantly different from previous studies of infinitely lived asset markets. There is only one change in the dividend structure across treatments to create different fundamentals which allows me easily compare market outcomes. There are four Market Treatments: 1) Constant Fundamentals with Terminal Value, 2) Constant Fundamentals without Terminal

[4] I use the terminal value and buy back value interchangeably in order to refer to the assets which are convertible into cash at the end of a market game depending on the experimental design.

Value, 3) Decreasing Fundamentals, 4) Increasing Fundamentals.

Experimental data indicate significant underpricing of assets with bankruptcy risk if there is a lack of buyback value. Only constant fundamental value assets, backed by a terminal value, reveal price convergence in indefinite horizon markets. Combining results with Kirchler et al. (2012)(74), this study reveals that both definitely lived and indefinitely lived markets have price convergences for an asset supported by a buy back value. However, independent of fundamental value paths (constant, decreasing, increasing), indefinitely lived asset markets without a terminal value experience mispricing of the asset in most markets. Unlike most previous findings of finite horizon market experiments, this study reports undervaluation of assets in some markets with decreasing fundamentals. Moreover, I discuss risk aversion, time-varying perceptions of risk, biased belief formation of subjects and price anchoring as potential explanations for the undervaluation of assets in the indefinite horizon. The next section discusses the related experimental literature in detail. Then, I describe the experimental set-up and design details. After discussing the results and presenting the data analysis, I conclude.

1.2 RELATED LITERATURE

There is an extensive theoretical, empirical and experimental research on the efficiency of asset markets. Theoretical models focus on transaction prices as a means of information transmission in financial markets, but there is a dearth of empirical evidence due to a lack of precise conclusions since statistical criteria may fail to capture crucial insights of asset markets (Sunder (1995)(112)). Field data and/or theoretical models alone cannot lead to full understanding of the phenomena of bubbles and crashes in asset markets. Laboratory experiments allow researchers to induce fundamentals and compare those with actual prices, which are not possible in the field[5]. This paper relates to two branches of the literature on experimental asset markets and aims to set up a bridge between them by providing a direct comparison between definitely lived and infinitely lived asset markets with different

[5] Porter and Smith (2003, p. 7)(101) indicated an advantage of experimental tools: “In the economy, control over fundamental value and investor information is rarely possible and therefore minimal conditions for studying the role of expectations in stock market valuations cannot be identified.”

fundamental values. First, I provide a review of the literature on finite time horizon asset market experiments and then I focus on indefinitely lived asset market experiments.

The efficient market hypothesis[6] implies that all relevant information in a market should be reflected by transaction prices and thus, prices should be consistent with fundamentals. However, there is significant evidence suggesting that asset prices deviate from market fundamentals. The classic work of Smith et al. (1988)(108) reported that in an asset trading environment with a finite time horizon and a stochastic dividend structure, more than half of market experiments created price bubbles, "trade in high volumes at prices that are considerably at variance from intrinsic values" (King et al. (1993)(72), p. 2), followed by crashes relative to fundamental value. While observing price bubbles in experimental markets, many studies focused on checking robustness of them to different institutions and treatments[7].

Literature on experimental asset markets mainly focused on markets with declining fundamental values. However, assets may follow different fundamental value paths depending on their type and properties. A more realistic approach is the consideration of other paths, such as stochastic, and increasing fundamentals as noted by Oechssler (2010)(94) and Smith (2010)(107). Some studies focused on this issue and investigated asset markets with flat and increasing fundamentals. Although the payment of a single dividend at the end of a trading horizon reduced size of bubbles, markets with constant fundamental values still experienced bubbles (Caginalp et al. (1998)(16); Smith et al. (2000)(109); Noussair et al. (2001)(92); Bostian et al. (2006)(12); Bostian and Holt (2009)(11)). However, Kirchler et al. (2012)(74) and Huber et al. (2012)(62) reported price convergence in a constant fundamental value environment with fixed horizons. Davies (2006)(33) and Huber et al. (2012)(62) considered

[6] See Fama (1970)(40) for a review.

[7] Some studies tested treatments such as transaction fees, limiting price changes, using call markets, changing cash to asset ratio, having experienced traders, eliminating speculation, employing tâtonnement pricing mechanism (King et al. (1993)(72); Caginalp et al. (2001)(15); Porter and Smith (2003)(101); Lei et al. (2001)(77); Dufwenberg et al. (2005)(37); Lugovskyy et al. (2011)(82)). Many treatments did not help eliminate price bubbles with exception of short sales which induced underpricing for a declining fundamental asset (Haruvy and Noussair (2006)(57)). However, Caginalp et al. (2001)(15) showed that an asset market bubble may be reduced by simultaneous existence of low cash to asset ratio, deferred dividends and a publicly open bid-ask book. Another effective treatment in significantly eliminating price bubbles was experienced traders (Porter and Smith (2003)(101); Lei et al. (2001)(77); Dufwenberg et al. (2005)(37); Hussam et al. (2008)(63)). Moreover, detailed and careful introduction of asset market environment and framing of fundamental value process are shown to be effective in reduction of price bubbles in experimental asset markets (Lei and Vesely (2009)(78); Cheung et al. (2010)(25); Kirchler et al. (2012)(74)).

a finitely lived asset market with increasing fundamental value. Both papers indicated persistent undervaluation (negative bubble) of an asset with increasing fundamentals. On the other hand, Caginalp et al. (2002)(17) reported price bubbles for an increasing fundamental value asset when the asset coexisted with a speculative asset in the market. They showed that prices converge to fundamentals when two non-speculative assets are simultaneously traded. Another study, by Noussair and Powell (2009)(91), reported price bubbles for an asset market with non-monotonic fundamentals. Finally, Giusti et al. (2012)(49) observed price convergence for an asset with increasing fundamentals induced by the existence of interest payments on cash holdings.

There are fewer studies which focus on indefinitely lived asset markets. Camerer and Weigelt (1993)(18) reported mixed results on price convergence in a market for an asset with indefinite life-time and constant fundamental value regime. Their data revealed slow price convergence to fundamental values from below for some markets whereas others had price bubbles. Similarly, Ball and Holt (1998)(6) observed overpricing for an indefinitely lived asset with constant fundamentals and bankruptcy risk. Both studies employed an asset-specific bankruptcy risk, which led to different survival periods for different assets unlike the current experiment. However, Ball and Holt (1998)(6) reported results from a group decision making experiment since there were five trading teams in their asset market. In a more recent study, Hens and Steude (2009)(60) observed an asset market with constant fundamental value and found mixed results on price convergence. A session exhibited price bubbles similar to Ball and Holt (1998)(6) whereas some revealed undervaluation of the asset. Finally, Duffy and Crocket (2010)(30) applied an indefinite horizon experiment in which subjects trade an asset with a bankruptcy risk to smooth consumption. They observed both positive and negative bubbles due to treatment effects. It should be noted that each of these previous studies had its own focus and there were significant experimental design differences across these studies such as number of traders, dividend structure, number of trading periods, bankruptcy determination rule, provision of a buyback value, subject pool, etc. Thus, a comparison of results across these studies is difficult.

This study aims to identify the effects of different fundamental value regimes on price convergence for assets with bankruptcy risk by using a systematic and comparable set up.

Unlike Ball and Holt (1998)(6), the experimental design in this study consists of a stochastic dividend process and a random number of trading rounds leading to an indefinite life for all assets. Moreover, I introduce constant fundamentals with no terminal value as well as increasing and decreasing fundamental value trends in indefinitely lived asset markets which existed neither in Camerer and Weigelt (1993)(18) nor in Hens and Steude (2009)(60). The baseline treatment uses design of Kirchler et al. (2012)(74). Thus, the dividend process and information structure are significantly different from earlier studies of infinitely lived asset markets. Table 1[8] summarizes experimental design and illustrates related literature[9]. There are four treatments which allow a comparison of results across different fundamental value regimes. Treatment 1 helps with identifying effects of bankruptcy risk on bubble measures compared to that of a flat value asset lacking bankruptcy risk. I compare the data of Treatment 1 with a flat fundamental value treatment of Kirchler et al. (2012)(74), which is called Treatment 0 in this paper, to provide a comparison between a definite horizon market and markets with indefinite horizons. Treatment 2 drops the terminal value of the asset and adds a dividend structure with positive expected payment. By comparing Treatments 1 and 2, I differentiate between assets with and without terminal value. Only the dividend structure changes across these two treatments keeping fundamental value constant. Another contribution of my experimental design is to consider declining and increasing fundamental values in an indefinitely lived asset market byTreatment 3 and Treatment 4. Thus, this paper complements the literature by providing comprehensive experimental results on asset markets with different fundamental value trends in indefinite horizon.

[8](1) KHS (2012): Kirchler et al. (2012)(74); (2) NRR (2001): Noussair et al. (2001)(92); (3) CPS (1998): Caginalp et al. (1998)(16); (4) CIPS (2002): Caginalp et al. (2002)(17); (5) BH (1998): Ball and Holt (1998)(6); (6) HS (2009): Hens and Steude (2009)(60); (7) CW (1993): Camerer and Weigelt (1993)(18); (8) SSW (1998): Smith et al. (1988)(108); (9) KSWV (1993): King et al. (1993)(72);(10) NP (2009): Noussair and Powell (2009)(91); (11) SVBW (2000): Smith et al. (2000)(109); (12) HKS (2012): Huber et al. (2012)(62).

[9]Existence of bubbles in a definitely lived asset market with decreasing fundamentals is a robust finding and replicated by many other studies. I cite only two early papers here.

Table 1: Experimental Design and Related Literature

Fundamental Value				
Time Horizon	Constant with TV	Constant without TV	Decreasing	Increasing
Fixed	*Treatment 0* KHS (2012) NRR (2001)	SVBW (2000) CPS (1998)	SSW (1988) KSWV (1993) Others	Davies (2006)(33) NP (2009) CIPS (2002) HKS (2012)
Indefinite	*Treatment 1* BH (1998)	*Treatment 2* HS (2009) CW (1993)	*Treatment 3*	*Treatment 4*

1.3 EXPERIMENTAL DESIGN

120 students from the Pittsburgh Experimental Economics Laboratory (PEEL) subject pool are recruited for this study. There are 12 sessions, each with 10 participants. Each subject is allowed to participate in only one session. The experiment is conducted with z-Tree (Fischbacher (2007)(44)) and I modified the software code used by Kirchler et al. (2012)(74). Subjects are provided with instructions which include information on trading mechanisms, the dividend structure, fundamentals and bankruptcy determination rules[10].

The study uses a between-subject design by having different subjects for each treatment session with ten traders. Each trader has an endowment portfolio to start. There are two types of endowments: experimental cash and assets, A. Subjects start with one of the following endowment types: Endowment 1=(20A,3000) or Endowment 2=(60A,1000). Thus, half of the subjects start with the same endowment randomly assigned by the computer. The trading mechanism is a Double Auction in which sellers and buyers have the options to make asks and bids. Depending on the duration of a market, subjects may participate in more than one market in the session. If there is a market re-start, endowments are randomly re-assigned. Participants earn experimental currency during the market game(s) and these are converted into dollars for real payment at the end of a session. If a subject participates

[10] Experimental instructions include all relevant information and a multiple choice quiz to check subjects' understanding of market conditions. Subjects are given time to complete their answers for the quiz and the experimenter checks their answers to make sure that they get correct answers and enhance their understanding. A sample of instructions is provided in Appendix.

in more than one market, one/two of the markets is/are randomly chosen for payment. In addition to earnings from market(s), participants receive a show-up fee.

This study formulates the main hypothesis for price convergence in all markets according to the efficient market hypothesis. This theory assumes that investors react quickly to new information in a market and *rational expectations* exist. Then, updated information is reflected in prices and market fundamentals. Moreover, I calculated the expected value of future payments from an asset under the assumption of *risk-neutrality*.

Main Hypothesis: *Prices follow fundamentals in asset markets with bankruptcy risk.*

The fundamental value (FV) of an asset for period t is determined by the following equation: $FV(t) = TV + \sum_{s=t}^{T} r^{s-t} E(d_s)$, where $E(d_s)$ is the expected dividend for the asset at period $t = 1, 2, 3, ..., T \epsilon \{10, \infty\}$ and TV is the terminal value.

1.3.1 Treatment 0: Fixed Horizon-Constant Fundamentals with Terminal Value

Treatment 0 is the flat fundamental value treatment of Kirchler et al. (2012)(74), which has 10 trading periods. An asset of this market has two types of equally likely dividend payments: $\{-5, 5\}$ with an expected dividend of zero. In addition to dividend payments, an asset has a terminal value of 50 experimental cash to be collected at the end of a market. Thus, the fundamental value of an asset is constant at 50 for each period. I used data from this previous experiment for comparison and provide a detailed analysis in Appendix[11].

1.3.2 Treatment 1: Constant Fundamentals with Terminal Value

Treatment 1 introduces bankruptcy risk into Treatment 0 leading to an indefinite number of trading periods. For each market, Treatment 1 has 8 trading periods in expectation. A market has an extra trading period with a probability of 87.5%. After each trading period, there is an 8-sided die roll by participants to determine the assets' life-time. If the die roll reads 1, then all assets are worthless and the market ends. Namely, an asset market is closed

[11] One may argue that results across two studies may not be comparable due to experimenter fixed effects and/or subject pool effects. However, I already observe price convergence in Treatment 1 which is an indefinite version of Treatment 0. Given that the PEEL subjects follow fundamentals for pricing an asset in this indefinitely lived market, they will easily figure out pricing an asset in fixed horizon markets. Thus, I choose not to replicate findings of Kirchler et al. (2012)(74) but use their data for comparison.

with probability of 12.5%. Then, the continuation probability of a market is $r = 0.875$, which generates an expected duration of eight periods[12]. An asset still has a terminal value of 50 if a market ends. Thus, the fundamental value of an asset is 50 for any period. Since the expected dividend payments are zero for each period, the fundamental value of an asset is equal to its terminal value. Thus, the results of this treatment can be compared with Treatment 0.

1.3.3 Treatment 2: Constant Fundamentals without Terminal Value

Using positive expected dividend payments, this treatment considers a flat fundamental value for the asset which is not supported by a terminal value. Unlike Treatment 1, the terminal value is replaced by positive expected dividend payments. An asset has two types of equally likely dividend payments: $\{0, 12\}$. The continuation probability is $r = 0.875$ and the expected duration of a market is still eight periods. For any period t, the fundamental value of an asset is given by: $FV(t) = \sum_{t=1}^{\infty} r^{t-1} E(d_t) = \sum_{t=1}^{\infty} 6(\frac{7}{8})^{t-1} = \frac{6}{1-(7/8)} = 48$. Thus, the fundamental value of an asset in this treatment is 48 EC for any period.

1.3.4 Treatment 3: Decreasing Fundamentals

This treatment is identical with Treatment 2, except for the dividend process. In each period, the expected dividend of an asset is declining, inducing an infinitely lived asset with declining fundamentals. A market has a continuation probability of $r = 0.875$ and an expected duration of eight periods. The time-varying dividend structure is illustrated in Table 2. The expected dividend is determined by $E(d_t) = \frac{1}{2}(57 - t)$ and the fundamentals are given by $FV(t) = 200 - 4t$ for any period t. The fundamental value of an asset without a terminal value for a given period t is given by the following: $FV(t) = \sum_{s=t}^{\infty} r^{s-t} E(d_s)$, where $E(d_s)$ is expected dividend for an asset at period $t = 1,\ 2,\ 3,...$

An asset in Treatment 3 has a declining fundamental value trend and exhibits the following expected dividend payments for any period s: $E(d_s) = \frac{1}{2}(57 - s)$.

[12] $Expected\ Duration = \frac{1}{1-r} = \frac{1}{1-0.875} = \frac{1}{0.125} = 8.$

Table 2: Average Holding Value: Treatment 3

Period	Expected Dividend	Dividend Set	Fundamental Value
1	28	{0,56}	196
2	27.5	{0,55}	192
3	27	{0,54}	188
4	26.5	{0,53}	184
5	26	{0,52}	180
...	...	...	...
10	23.5	{0,47}	160
...	...	...	...
15	21	{0,42}	140
...	...	...	...
21	18	{0,36}	116
...	...	...	...
25	16	{0,32}	100
...	...	...	...
29	14	{0,28}	84
...	...	...	...

Combining equations, one obtaines: $FV(t) = \frac{57}{2} \sum_{s=t}^{\infty} r^{s-t} - \frac{1}{2} \sum_{s=t}^{\infty} r^{s-t} s$. Reparametrizing $m = s - t$ and using $\sum_{m=0}^{\infty} r^m = (\frac{1}{1-r})$, $\sum_{m=0}^{\infty} m r^m = \frac{r}{(1-r)^2}$, I write: $FV(t) = \frac{58-t}{2(1-r)} - \frac{1}{2(1-r)^2}$. Finally, for $r = 0.875$, one obtains: $FV(t) = 200 - 4t$.

1.3.5 Treatment 4: Indefinite Life-Increasing Fundamentals

This treatment is identical with Treatment 3 except for the dividend process. In each period, the expected dividend of an asset is increasing unlike Treatment 3 and this structure induces an infinitely lived asset with an increasing fundamental value. A market has the same continuation probability of $r = 0.875$ and an expected duration of eight periods. The time-dependent dividend structure is illustrated in Table 3. The expected dividend is given by $E(d_t) = \frac{1}{2} t$ and fundamentals are calculated as $FV(t) = 28 + 4t$ for any period t. The fundamental value of an asset is calculated by following the steps of the previous section. An asset in Treatment 4 has an increasing fundamental value trend and exhibits the following expected dividend payments for any period s: $E(d_s) = \frac{1}{2} s$. Combining the fundamental value and the expected dividend equations, one obtains: $FV(t) = \frac{1}{2} \sum_{s=t}^{\infty} r^{s-t} s$.

Table 3: Average Holding Value: Treatment 4

Period	Expected Dividend	Dividend Set	Fundamental Value
1	0.5	{0,1}	32
2	1	{0,2}	36
3	1.5	{0,3}	40
4	2	{0,4}	44
5	2.5	{0,5}	48
...	...	...	...
10	5	{0,10}	68
...	...	...	...
15	7.5	{0,15}	88
...	...	...	...
21	10.5	{0,21}	112
...	...	...	...
27	13.5	{0,27}	136
...	...	...	...
37	18.5	{0,37}	176
...	...	...	...

Reparametrizing $m = s - t$ and using $\sum_{m=0}^{\infty} r^m = (\frac{1}{1-r})$, $\sum_{m=0}^{\infty} m r^m = \frac{r}{(1-r)^2}$, I write: $FV(t) = \frac{r}{2(1-r)^2} + \frac{t}{2(1-r)}$. Finally for $r = 0.875$, one obtains: $FV(t) = 28 + 4t$.

1.4 EXPERIMENTAL RESULTS AND DATA ANALYSIS

I analyze experimental data using different measures for comparison of prices with fundamental values. First, the main hypothesis is tested by paired t and Wilcoxon signed-rank tests. I also present two bubble measures suggested in the literature (Stockl et al., 2010(111)). Then, the figures of all transaction prices, the median, the mean and the last transaction price are plotted for each session. Finally, I discuss the portfolio adjustments of traders.

1.4.1 Tests, Bubble Measures and Portfolio Adjustments

Statistical test results mostly indicate that prices are significantly different from fundamentals for assets with bankruptcy risk, regardless of the fundamental value path. Since prices and fundamentals are not independent in asset markets, I employ comparison tests for dependent samples. Table 4 provides paired t-test and Wilcoxon signed-rank test results for the main hypothesis. The fourth row reports the results of paired t-test comparing all transaction prices with fundamental values of the corresponding session. In the fifth row, I report results of Wilcoxon signed-rank test for the difference of transaction prices and fundamental values. The seventh and eight rows indicate test results using weighted mean prices as a price measure for each trading period of markets. I use data for the two longest markets for each session. For instance, the first two sessions of Treatment 2 have only one market. In all sessions of Treatment 2 and Treatment 4, multiple markets are observed. For most markets, transaction prices significantly differ from fundamentals according to Table 4. However, rows seven and eight indicate that the weighted mean prices of the first markets are not statistically different from the fundamentals for some sessions such as the third session of Treatment 1 and second sessions of Treatment 2 and Treatment 4. All second markets provide evidence to reject the main hypothesis of the experiment. Moreover, analysis of data for Treatment 0 indicate that there are also mixed results on price convergence for an asset with constant fundamentals in a fixed horizon market. Thus, test results provide partial evidence to reject the null hypothesis that prices follow fundamentals.

Price convergence in experimental asset markets is often evaluated by the criteria of bubble measures. Stockl et al. (2010)(111) asserted that measures of mispricing should change monotonically with respect to the differences among prices and fundamental values. The authors also discussed that *Relative Absolute Deviation* and *Relative Deviation* are independent of total number of trading rounds and absolute level of fundamentals.[13] Since this paper considers markets with different numbers of trading periods and different fundamental value paths, these two measures are appropriate for comparing different treatments. Relative absolute deviation (RAD) indicates aggregate level of mispricing. "RAD is easy to interpret, as e.g., a value of 0.10 means that on average mean prices per period differ 10 percent from the average fundamental value in the market" (Stockl et al., 2010(111), p. 290). Relative deviation (RD) considers thr raw difference between the fundamentals and the weighted mean prices and measures overvaluation of an asset in a market. A positive (negative) value of RD indicates an overvaluation (undervaluation).

[13] $RAD = \dfrac{1}{N}\sum_t \dfrac{\left|(\overline{P_t^w} - FV_t)\right|}{\left|\overline{FV}\right|}$ $RD = \dfrac{1}{N}\sum_t \dfrac{(\overline{P_t^w} - FV_t)}{\left|\overline{FV}\right|}$, where N is total number of trading periods, $\overline{FV}$ is mean fundamental value in a market and $\overline{P_t^w}$ is volume-weighted mean prices.

Table 4: Paired t and Wilcoxon signed-rank tests: All Transaction Prices, Weighted Mean Prices, Fundamental Values: t and z values

	H_o: Prices=Fundamentals											
	Treatment 1			Treatment 2			Treatment 3			Treatment 4		
Market 1	Session 1	Session 2	Session 3	Session 1	Session 2	Session 3	Session 1	Session 2	Session 3	Session 1	Session 2	Session 3
t(all)	-7.03***	-5.13***	2.03**	-43.40***	-1.81	-1200***	-18.90***	6.47***	-34.74***	-5.09***	0.36	-12.96***
z(all)	-7.76***	-5.33***	3.48***	-7.63***	-1.80	-13.78***	-13.11***	9.19***	-10.97***	-4.24***	-0.49	-8.01***
N	229	106	98	77	107	251	338	572	160	60	110	108
t(mean)	-6.80***	-1.91*	-0.50	-42.15***	0.09	-26.58***	-3.24***	-0.137	-8.20***	-1.27	0.32	-4.45***
z(mean)	-2.93***	-2.38**	0.00	-2.02***	-2.22**	-2.66***	-2.41**	0.928	-2.52**	-0.94	0.00	-2.70***
N	11	8	8	5	5	9	21	25	8	5	7	10
Market 2												
t(all)	-18.49***			-1200***	-84.34***	-1700***			-35.87***	-21.10***	-29.86***	-21.17***
z(all)	-15.03***			-11.16***	-13.99***	-11.23***			-16.74***	-11.11***	-13.67***	-8.14***
N	320			165	260	167			398	189	262	88
t(mean)	-8.36***			-35.10***	-21.68***	-75.82***			-7.81***	-5.93***	-7.17***	-5.98***
z(mean)	-3.05***			-2.66***	-2.66***	-2.02***			-3.40***	-3.04***	-3.11***	-2.52**
N	12			9	9	5			15	13	13	8

Notes: 1) I consider longest two markets of each session, if available. 2) * p<0.1, ** p<0.05, ***p<0.1

Table 5 indicates bubble measures for sessions of each treatment. Most markets exhibit underpricing of the assets since all RD values are negative except the initial markets in the second sessions of treatment two and treatment four. Measures for markets with constant fundamentals backed by terminal values indicate that there are small deviations from fundamentals compared to other treatments. In the first treatment, the average transaction price per period deviate by 1% from the average fundamental value of assets in session two and session three. In treatment zero, price deviations are less than 5% except for session four which exhibits a RAD value of 0.36.[14] Although deviations from fundamentals are statistically significant for some markets as indicated by the previous table, bubble measures indicate that these differences are very small.[15] In sum, for most markets, transaction prices closely follow fundamentals for assets supported by a buy back value under bankruptcy risk. For constant fundamental value assets without buy back value, results indicate large deviations from fundamentals. RAD values of this treatment range from 0.42 to 0.72. Overall, bubble measures provide evidence for negative price bubbles in this treatment. Results for markets with decreasing fundamentals provide mixed results. The first and last sessions indicate existence of underpricing and large price deviations whereas second session reveals price bubbles after sixth period. The lowest RAD of the treatment is 0.24 whereas in the first market of session three, RAD reads 0.56. Finally, in treatment four, price divergence is observed for the markets with increasing fundamentals. RAD values of this treatment range from 0.21 to 0.63. Second markets exhibit higher deviations with RADs over 40%. In sum, most markets without terminal value mostly exhibit large undervaluation of the asset (i.e. negative price bubble).

1.4.2 Treatment 1: Constant Fundamentals with Terminal Value

In the first session of this treatment, I observe two markets. The first one lasts 11 periods whereas the second one has 12 trading rounds. After the first one, subjects participate in the second one by getting their randomly assigned portfolios. Thus, participants experience a market restart with possibly different endowments. In late periods of the second market, the

[14] See Appendix for Treatment 0 analysis.

[15] For instance, the hypothesis that prices are equal to 49.5 is not rejected for session two of treatment one.

Table 5: Bubble Measures

	Treatment 1			Treatment 2			Treatment 3			Treatment 4		
Market 1	S1	S2	S3	S1	S2	S3	S1	S2	S3	S1	S2	S3
RAD	0.06	0.01	0.01	0.60	0.42	0.72	0.46	0.24	0.59	0.21	0.41	0.30
RD	-0.06	-0.01	-0.003	-0.60	0.02	-0.72	-0.34	-0.009	-0.59	-0.13	0.07	-0.29
N	11	8	8	5	5	9	21	25	8	5	7	10
Market 2												
RAD	0.02			0.54	0.60	0.70			0.45	0.49	0.44	0.63
RD	-0.02			-0.54	-0.60	-0.70			-0.45	-0.47	-0.43	-0.63
N	12			9	9	5			15	13	13	8

Notes: 1) I consider longest two markets of each session, if available. 2) S1=Session1, S2=Session2, S3=Session3.

continuation probability, i.e. the bankruptcy risk, is changed. Namely, at period 20 and 22, the market ending probability is increased to 25% and 37.5% respectively.[16] In all figures, the market changes are shown by a black long-dashed line whereas the market ending probability changes are shown by a gray short-dashed line. Figure 1 reveals the transaction prices for each period. The variance of transaction prices is higher in the first market than in the second. Except for a couple of observations in the early trading periods, transaction prices are close to fundamentals in these markets. Prices converge to fundamentals from below. In the second and third sessions, similar price movements are observed. The second part of Figure 1 indicates the mean, the median and the last price of trading periods in this session. The paths of these statistical indicators of prices are also close to fundamentals. Thus, as long as an asset is backed by a terminal value, prices follow fundamentals for an asset with a flat fundamental value regime under bankruptcy risk. However, traders accept prices lower than the terminal value in compensation for avoiding the risk of receiving negative dividends.

The results of this treatment are consistent with those provided by Kirchler et al. (2012)(74) as these authors observe price convergence in a finite version of the treatment. This study provides a robustness check and indicate that even in an indefinitely lived asset market, constant fundamentals supported by terminal value exhibit price convergence from below. Bankruptcy risk does not impact on price convergence since subjects are guaranteed

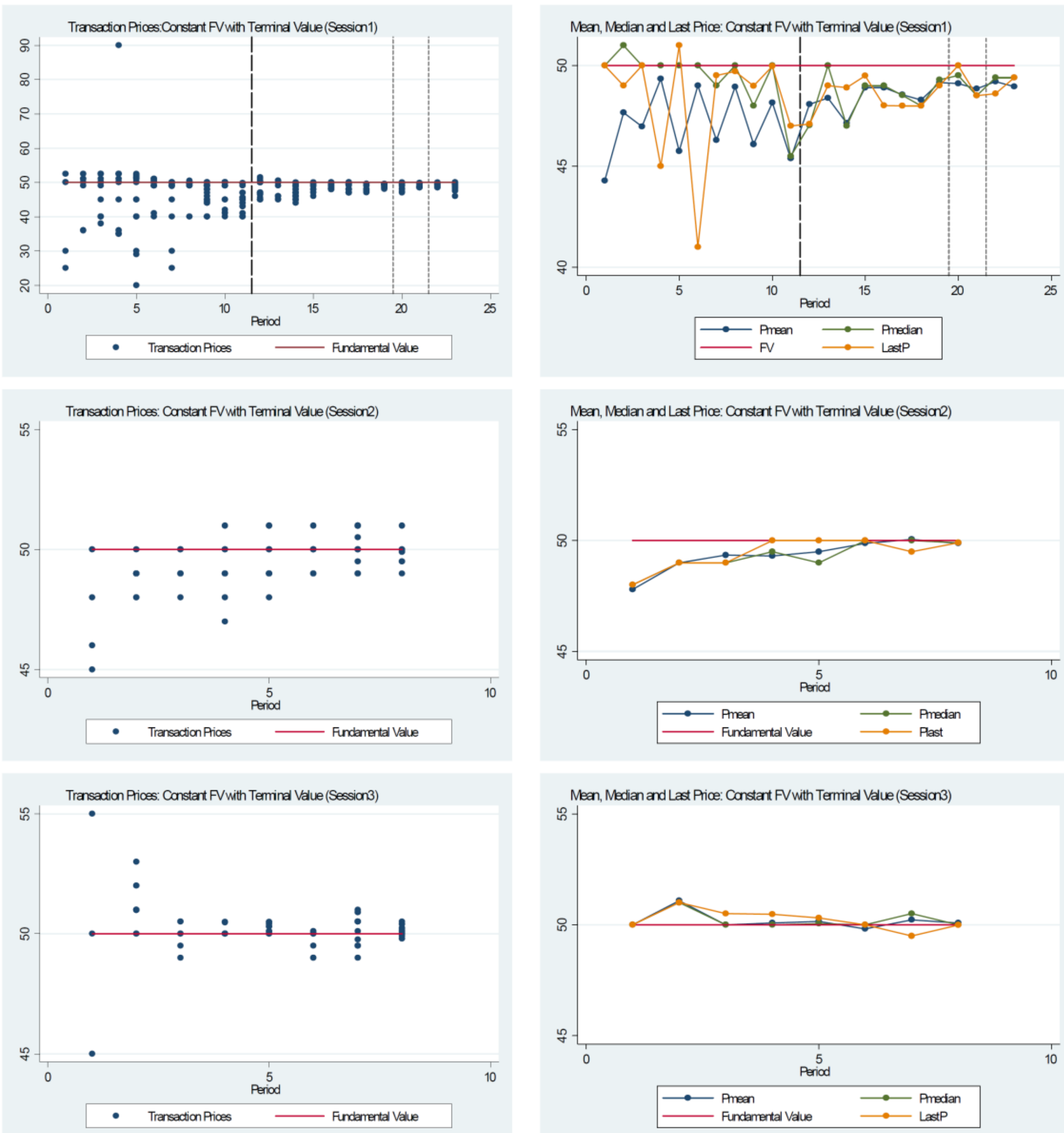
[16] A change in bankruptcy risk does not impact fundamentals in this market. However, I calculate the effect of changing continuation probability on fundamentals in Treatment 3 and Treatment 4, which are given in Appendix. This feature of experimental design incorporates time-varying discount rates in asset markets as discussed by Cochrane (2011)(27).

to get a terminal value for an asset. Finally, in markets of the first session, two subjects preferred to hold higher numbers of assets whereas another two held very low numbers of assets. During the second market, period 19, the number of assets held by two participants was 42% of total assets. Portfolio holdings in other markets are relatively balanced in this treatment. In the first market of the second session, two subjects held 35% of the total assets at the end. The highest share for the total assets held by two participants in the first market of the third session is 41%. Thus, the distribution of assets among traders was fairly balanced in this treatment.

1.4.3 Treatment 2: Constant Fundamentals without Terminal Value

In the first session, subjects participate in five markets. The second session reveals data for two markets and the last session consists of three markets. Transaction prices are less volatile in the later markets of all sessions. This is evidence for a market restart effect on market prices. Subjects employ their past knowledge to make decisions in the new markets. However, this behavior does not help prices catch up with the fundamentals. Except fo a couple of periods in the early markets, transaction prices are significantly lower than fundamentals in markets of this treatment. Figure 2 plots transaction prices for assets of this treatment. The mean, the median and the last price of periods move together and they are far below fundamentals except in early markets of the first and second session. The absence of a terminal value has a dramatic impact on pricing behavior traders. Risk of getting a worthless asset at the end of a market leads traders to accept lower prices. The mean and the median prices fluctuate between 6 and 24, half and twice of the positive dividend payment, 12. Coupled with the absence of the buyback value, the bankruptcy probability leads to an underpricing of an asset. Subjects are likely to overweight the bankruptcy risk especially after experiencing a default for the assets they hold. Moreover, the data on asset holdings of participants reveal extreme portfolio choices in this environment. In the second market of first session, the total number of assets held by two participants was 219, more than 50% of total assets. At the end of fifth market, period 20, one participant holds 70% of the total assets. Similarly, in the second market of the second session, 62% of the total assets is held

Figure 1: Trading Prices for Treatment 1 (Constant Fundamentals with Terminal Value)



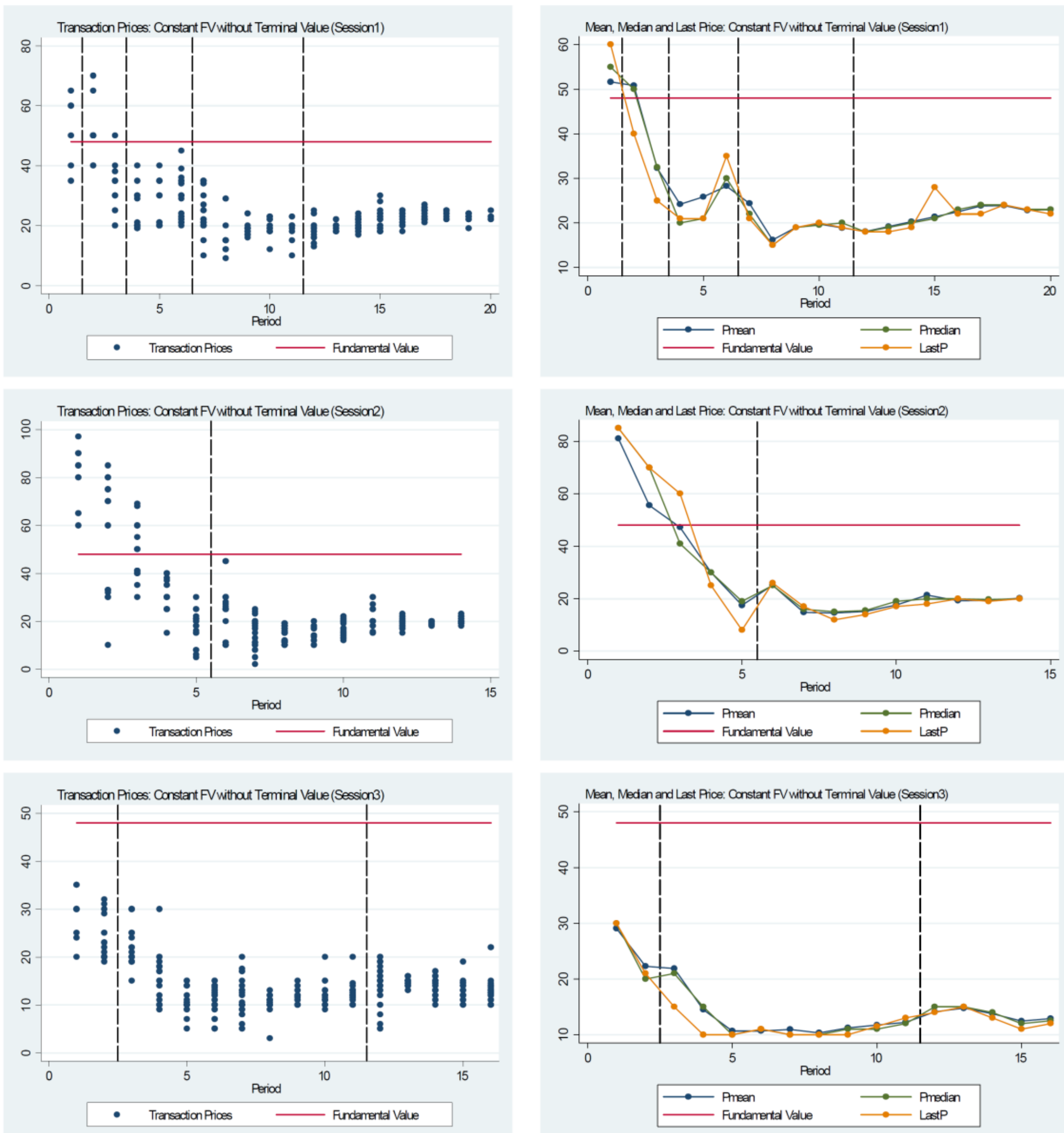
by two participants. Finally, at the end of the second market in session three, the number of assets held by one participant is 314 (79% of the total assets).

1.4.4 Treatment 3: Decreasing Fundamentals

Treatment 3 yields mixed results. The first session starts with a one period market and the second market lasts longer for 21 periods. In the late periods of the second market, the continuation probability is lower. Namely, at period 17 and 21, the market ending probability is increased to 25% and 37.5% respectively.[17] Figure 3 reveals all transaction prices, the mean, the median and the last price for each period. The variances of transaction prices decrease over time. Similar to the previous treatments, there is evidence for a restart effect on market outcomes. In most trading periods, transaction prices are lower than the fundamental value of an asset with a declining fundamental value path. The mean, the median and the last price of periods have similar trends and move below fundamentals. During the middle periods of session one, transaction prices settle down around 70, which is less than the adjusted fundamental values. As the fundamentals decline, unlike in the finite horizon markets, this session reports underpricing initially and end of market price bubbles. In the third session, the level of prices is higher than in the first session. However, both markets of this session exhibit prices which are still significantly below the fundamentals. The second session exhibits the highest prices of this treatment in a long duration market. The trading prices are below fundamentals during the early periods. After the sixth period the market generates a positive bubble with a relative deviation of 26%. Thus, the second session results are similar to previous bubble findings of declining fundamental value treatments in a fixed horizon. Unlike the stylized positive bubble and end of game crash finding of the literature in finitely lived treatments, asset market with decreasing fundamentals and bankruptcy risk yields a negative bubble in both the first and the last session. Similar to the second treatment, risks of having a worthless asset at the end of the market lead traders to accept trading at lower prices. Subjects may also have overweighted bankruptcy risk,

[17] Using original fundamental values, instructions state that there may be a change in bankruptcy risk. For the markets with changes in the bankruptcy risk, adjusted fundamental values are used in figures and tables. Approximations for fundamentals are shown in the Appendix.

Figure 2: Trading Prices for Treatment 2 (Constant Fundamentals without Terminal Value)



especially after experiencing a market end, leading to underpricing of an asset. There are unequal portfolio allocations in this treatment. In the second market of the first session, period 22, the number of assets held by two participants corresponds to 63% of the total assets. The second session generates more extreme results similar to Camerer and Weigelt (1993)(18). In the second market of this session, a participant collects 97% of the total assets, which may decrease the supply of assets and drive bubbles in the market. Finally, in the second market of session three, the number of assets held by two participants corresponds to 60% of the total assets.

1.4.5 Treatment 4: Increasing Fundamentals

The first session has four markets whereas the second and third sessions have three markets. The probability of bankruptcy is increased to 25% in late periods of the fourth market for the first session and the third market of second session. Figure 4 reveals the transaction prices, the mean, the median and the last price for each period. The volatility of transaction prices decreases over time in all markets of the treatment. Mean, median and the last price of the periods move together and they are significantly below fundamentals for many markets. In early trading periods of each session, prices start higher than the fundamentals. However, most markets experience negative price bubbles during the later periods. For instance, during the middle periods of the fourth market in session one, transaction prices settle down around eight. In the third market of the second session, prices are relatively stable around 12. The results of this treatment are consistent with the findings of the previous literature on finitely lived markets. Similar to the second and third treatments, the risk of ending up with junk assets leads traders to accept lower trading prices. Subjects probably overweight the default risk and price an asset on the basis of potential positive dividend payment of a period. Moreover, I observe many short markets in this session due to the design of the experiment.[18] Trading prices decrease as subjects experience a bankruptcy for their assets and thus, the restart worsens mispricing of an asset. Cash-to-asset ratio is increasing in these markets due to potential positive dividend payments. Thus, underpricing of an asset is more

[18] Die roll by participants determine bankruptcy and life of an asset. This set up has a tradeoff between running very short markets and having a convincing design for probabilistic duration of a market.

Figure 3: Trading Prices for Treatment 3 (Decreasing Fundamentals)

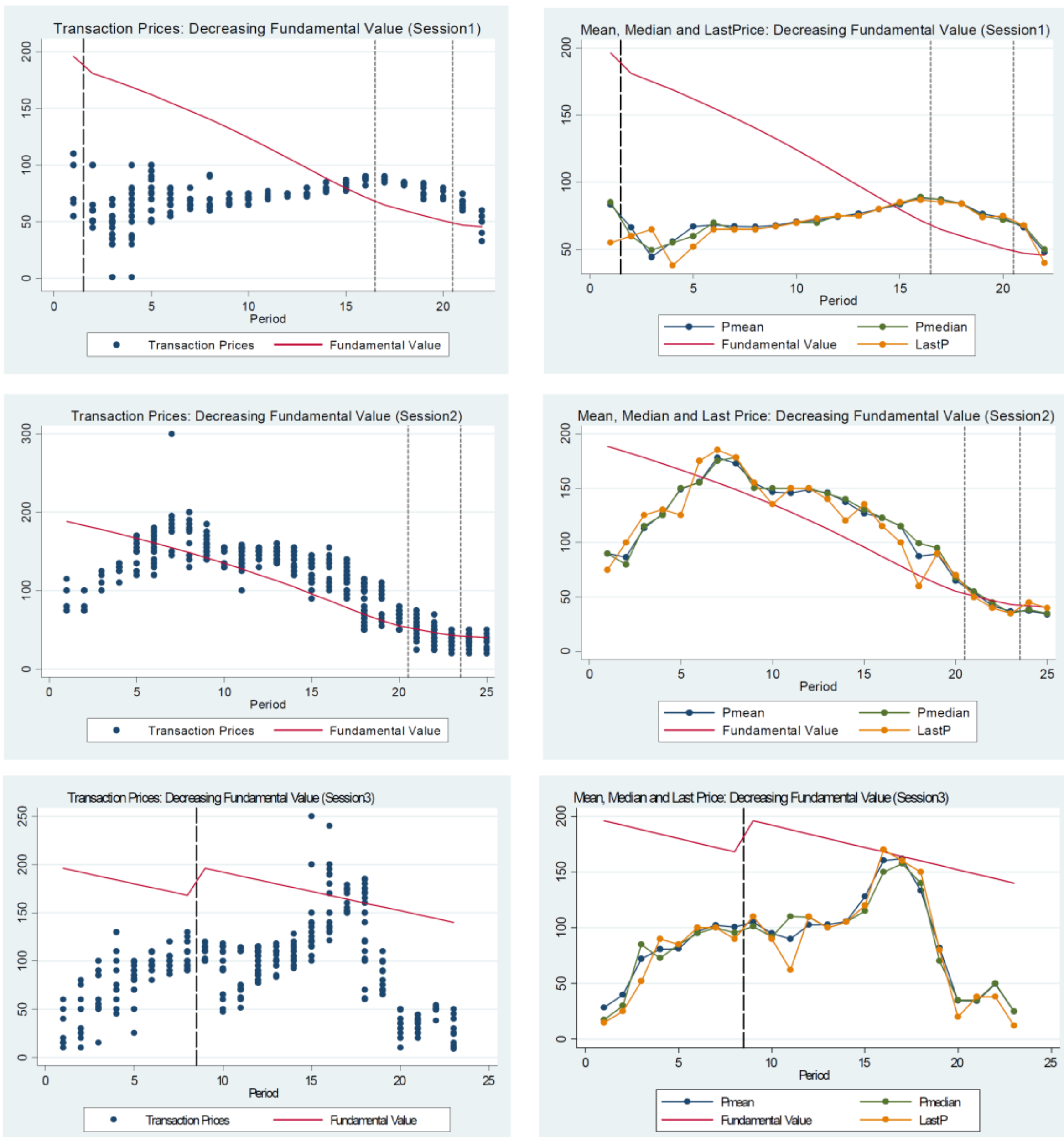


Figure 4: Trading Prices for Treatment 4 (Increasing Fundemantals)

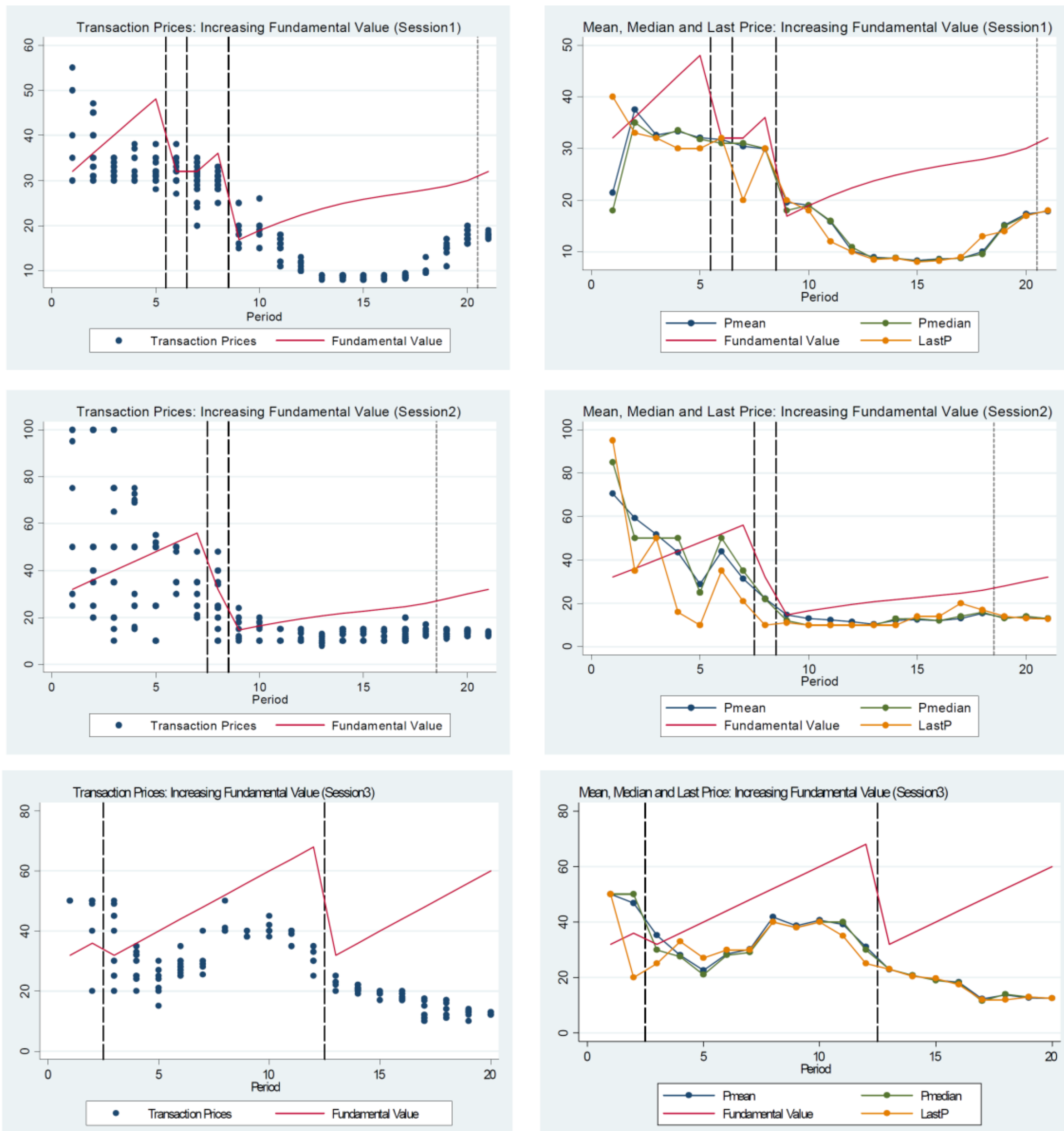


Table 6: Gini's Concentration Ratio for End of Market Asset Allocations

	Treatment 1			Treatment 2			Treatment 3			Treatment 4		
	S1	S2	S3	S1	S2	S3	S1	S2	S3	S1	S2	S3
Endowment	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25
Market 1	0.44	0.31	0.34	0.71	0.33	0.80	0.60	0.88	0.41	0.34	0.40	0.47
Market 2	0.43	-	-	0.77	0.61	0.73	-	-	0.57	0.61	0.62	0.53

Notes: 1) I consider the longest two markets for each session, if available. 2) S1=Session1. S2=Session 2. S3=Session3.

likely to have resulted from a bankruptcy experience effect rather than from a shortage of cash.

Unequal portfolio allocations are similar to previous asset markets without terminal value. During the fourth market of the first session, in period 18, the number of assets held by two participants corresponds to 75% of the total assets. Half of the participants held zero assets in this specific period. In the third market of session two, period 18, 69% of the total assets is held by two participants. Finally, in the last market of third session, the number of assets held by two participants was 220 (55% of the total assets).

1.4.6 Explanations for Results

Experimental data indicate significant underpricing for assets with bankruptcy risk if there is no buy back value. I suggest that risk aversion; time varying perceptions of risk; biased beliefs due to probability weighting and price anchoring are all explanations for this underpricing behavior in asset markets with indefinite duration.

As noted above, the portfolio allocations of traders are highly imbalanced in markets without a terminal value. In these markets, a small number of traders collect the majority of assets whereas many traders prefer holding a small amount of assets. In order to avoid bankruptcy, many participants quickly converted their assets into cash at low prices. The first explanation for this behavior of traders is risk preferences. Relying on a risk-neutrality assumption, expected fundamental value calculations do not account for heterogeneity in risk preferences of traders. The experimental design of this study does not include risk preference elicitation of subjects due to time and budget constraints. However, previous research reveals that risk preferences affect decision making in experimental asset markets. Fellner and Maciejovsky (2007)(41) reported that risk averse traders are less active in markets with fixed horizons. Risk averse agents submit fewer bids and asks and complete less trading contracts. Similarly, Robin et al. (2012)(102) found less mispricing lower asset turnover when the fraction of more risk averse participants is higher in a market. Moreover, Crockett and Duffy (2010)(30) showed that the number of shares acquired by subjects in an indefinitely lived market is affected by their Holt-Laury (2002)(61) risk tolerance measure. Crockett and Duffy (2010, p. 4)(30) noted the following:

"The higher prices in the linear exchange rate economies are driven by a concentration of shareholdings among the most risk-tolerant subjects in the market as identified by the Holt-Laury measure of risk attitudes. By contrast, in the concave exchange rate treatment, most subjects actively traded shares in each period so as to smooth their consumption in the manner predicted by theory; consequently, shareholdings were much less concentrated."

Table 6 shows Gini's concentration ratio for the end of market asset allocations in the two longest markets of each session. This measure of inequality lies between zero and one, where zero indicates equal distribution of assets among traders and one implies that a subject holds all the assets in a market. The first row indicates that the concentration ratio for endowment allocations is 0.25 for all treatments. The highest concentration ratio, 0.88, is observed in session three of treatment three. In treatment one, asset allocations are relatively more balanced compared to other treatments. Treatment two reveals concentration ratios higher than 0.60 except the first market of session two. The lack of a terminal value significantly affects trader's portfolio adjustments. Many second markets of treatment four exhibit more unequal allocations compared to the first markets of the same session implying that participants are inclined to prefer more extreme portfolio choices once they experience a bankruptcy of an asset. Thus, asset allocation data is consistent with the result of Crockett and Duffy (2010)(30) implying that risk preferences have a role in the decision making process of traders in asset markets with indefinite duration. Moreover, Croson and Gneezy (2009)(31) found that women are more risk averse than men. Given previous experimental findings on risk aversion and portfolio allocation, gender became an instrument for risk aver-

Table 7: OLS Results: Asset Holdings and Gender

	Treatment 1	Treatment 2	Treatment 3	Treatment 4
Female	9.00	-52.77**	-24.69	-18.88**
	[8.34]	[8.37]	[17.77]	[4.35]
Constant	34.60	21.05	55.20	25.94***
	[14.36]	[10.59]	[27.26]	[2.06]
R^2	0.023	0.202	0.042	0.078
N	40	60	40	60

Notes: 1) I pooled data of the longest two markets for sessions of each treatment, if available.

2) Each session has different number of trading rounds and different numbers of markets are observed.

3) All regressions include control variables for asset endowment, number of periods and number of female traders.

4) Standard errors (in parentheses) are clustered at session level. *** p<0.01, ** p<0.05, * p<0.1

sion in this study. Table 7 provides regression results for the end of market asset holdings and gender. The estimation results indicate a negative coefficient for a female dummy variable for markets without terminal value. Females are likely to hold more assets than men if there is a terminal value. A lack of terminal value led females to run away from assets under bankruptcy risk. Thus, on average, female participants hold fewer assets than men in most markets. Finally, time-varying perceptions of risk could have played a crucial role in the decisions of participants. Friedman and Kuttner (1992)(46) discussed that investor's perception for risks associated with holding different assets may change quickly due to subjective and/or objective factors. Similarly, Guiso et al. (2013)(53) indicated that measures of risk aversion for clients of Italian banks changes crucially after the 2008 financial crises. Authors found via experiment that this behavior is mostly resulted from an emotional response to a scary experience. Findings of the current experiment is consistent with Guiso et al. (2013) results. Participants of indefinite horizon markets exihibit different pricing behavior after experiencing a bankruptcy similar to behavior of bank clients in Italy.

Biased belief formation of participants may also have affected their decisions in this experiment. Subjects are faced with two types of uncertainty in this experiment: 1) Uncertainty of dividend payments and 2) Uncertainty of asset life, i.e. number of trading periods. Traders may overweight both bankruptcy risk and under/overweight the likelihood of dividend payments. For instance, mean and median prices of treatment two ranges from 6 to

24, half and twice of positive dividend payment. Subjects overweight bankruptcy risk and anticipate that the market will have one or two additional trading rounds although expected duration of a market is eight rounds after each die roll. Heterogeneity in perceived bankruptcy probabilities and biased beliefs of subjects lead different valuations of an asset among traders. Thus, prospect theory (Kahneman and Tversky, 1979(69)) may offer an explanation for the decision making of participants in markets for assets with bankruptcy risk.

Observing underpricing of an asset with increasing fundamentals, Huber et al. (2012)(62) discussed that "anchoring" is a strong explanation for price deviations in experimental asset markets[19]. The experimental set up of asset markets provides different information sets for the participants. First, before trading, subjects read instructions and absorb information on fundamental value processes, the properties of an asset, trading mechanism, payment rules and answer a questionnaire/quiz. Then, during trading rounds, subjects receive additional information such as bids, asks, transaction prices, trading history, dividend realizations. The second set of information plays a dominant role in traders' decisions since they get this information set more frequently. Thus, past prices are more likely to serve as an anchor compared to the fundamental value of an asset. Huber et al. (2012)(62) ran additional treatment in which they display fundamental values on trading screen and the data provide support for their explanation since they observe more efficient market prices. Moreover, by studying fixed horizon experimental markets Haruvy et al. (2007)(58) provided evidence that trader's beliefs about prices are mainly based on previous trajectories both in current and past markets in which they participated.

In the current experiment, I do not provide fundamental value information on the trading screen. However, the fundamental value table is shown on a screen in PEEL via the help of a projector during the experiment. In Table 8, I present OLS regressions for the current and past transaction prices as an evidence for price anchoring. Although fundamentals significantly correlate with prices, there is a significant relationship between the current and previous prices in most sessions. The coefficient for the first lag of transaction prices, ranging from 0.335 to 0.849, is positively significant for all treatments and all sessions. Similar to the

[19] Similarly, Caginalp et al. (2000)(14) also considered prices as an anchor and they discuss a momentum model which predict the changes transaction prices as a function of current price levels and fundamentals in an experimental asset market.

previous literature, there is strong evidence that prices serve as an anchor in this experiment. In sum, risk aversion, biased beliefs and price anchoring can explain the experimental results for significant undervaluation of the assets with bankruptcy risks. Finally, trading prices have a *path dependence* since participants follow past prices as an anchor and their decisions are crucially affected by previous experiences of bankruptcy. Path dependence is evidenced by large drops in prices following a bankruptcy.

1.5 CONCLUSION

Fragile financial systems increase debt defaults and bankruptcy risks, which significantly affect market functioning and social welfare. Investigating the efficiency of asset markets with bankruptcy risk, this study improves our understanding of individual incentives leading to bubbles and crashes. This study complements the literature by introducing asset markets with different fundamental value trends without a buyback value in indefinite horizon. Specifically, the first experimental results for indefinitely lived assets with increasing and decreasing fundamental value paths are presented. Data indicate negative price bubbles across a spectrum of different paths for fundamentals including rising, declining and stable regimes. Namely, regardless of a fundamental value regime, there is a significant underpricing of assets in most markets under a bankruptcy risk. Prices follow fundamentals for assets with a terminal value in a flat fundamental value regime for both the fixed and indefinite horizons, i.e. independent of bankruptcy risk.

In contrast to most previous finite horizon asset market experiments, this study also reports undervaluation of an asset in a decreasing fundamental value regime. Similar to most previous research, I report underpricing for an asset with increasing fundamentals. Moreover, experimental results indicate extremely unequal portfolio allocations in indefinitely lived asset markets. Faced with the risk of ending up with worthless assets and potentially overweighting the bankruptcy risk, most traders sell their assets at low prices. Additionally, portfolio allocations exhibit a gender effect implying that females are less likely to hold assets under bankruptcy risk. Time-varying risk perceptions and the path dependent behavior of traders may provide additional explanations for market outcomes in indefinite horizons.

Table 8: OLS Regressions: Current Prices, Fundamental Values, Past Prices

	Treatment 1			Treatment 2			Treatment 3			Treatment 4		
	Session 1	Session 2	Session 3	Session 1	Session 2	Session 3	Session 1	Session 2	Session 3	Session 1	Session 2	Session 3
Fundamentals	0.505***	0.522***	0.901***	0.0705***	0.0415***	0.0333***	-0.0284**	0.0855***	0.804*	0.0621**	0.170***	0.00516
	[0.0415]	[0.0804]	[0.109]	[0.0186]	[0.0140]	[0.00743]	[0.0133]	[0.0181]	[0.0411]	[0.0268]	[0.0538]	[0.0306]
$Prices_{t-1}$	0.410***	0.540***	0.373***	0.335***	0.775***	0.732***	0.700***	0.701***	0.788***	0.794***	0.849***	0.785***
	[0.0426]	[0.0992]	[0.0968]	[0.0454]	[0.0519]	[0.0464]	[0.0594]	[0.0410]	[0.0421]	[0.0552]	[0.0511]	[0.0689]
$Prices_{t-2}$	0.0649	-0.0653	-0.270***	0.524***	0.142***	0.154***	0.0594	0.207***	0.144***	0.142**	-0.0293	0.129*
	[0.0414]	[0.0874]	[0.0789]	[0.0454]	[0.0517]	[0.0464]	[0.0548]	[0.0405]	[0.0419]	[0.0549]	[0.0514]	[0.0686]
Constant							20.31***	1.557***	-7.38	-0.530*	-0.941	1.945
							[3.853]	[1.467]	[6.933]	[0.644]	[1.396]	[1.682]
R^2	0.99	0.99	0.99	0.95	0.94	0.97	0.61	0.92	0.87	0.92	0.77	0.82
N	547	104	96	354	365	454	344	570	556	325	386	211

Notes: 1) Each session is considered as a single market. 2) Each session has different number of trading rounds and different numbers of markets are observed.

3) Standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1

Similar to earlier experiments, there is evidence for price anchoring in asset markets with indefinite duration. Past transaction prices are crucial indicators for traders to decide on their bids and asks in double auction trading mechanisms. There is a significant relationship between current and previous period prices implying that the latter serves as an "anchor" for the former. Using experimental tools, we observe that the mispricing of an asset is formed independently of fundamentals in asset markets with indefinite duration if there is a lack of buy back value. Unlike the end of game crashes of finite horizon market experiments, assets with bankruptcy risk are significantly underpriced throughout whole market trading rounds. My findings imply that the efficient market hypothesis is not sufficient to predict market outcomes in indefinitely lived asset markets, i.e. for assets with bankruptcy risk. Assumptions of the efficient market hypothesis are violated by participants. First, traders do not react quickly to new information such as a market restart due to path dependency and price anchoring. Rational expectations assumption does not hold due to behavioral biases. Moreover, assuming risk-neutrality, fundamental value calculations do not account for heterogeneity in risk aversion of traders. Thus, behavioral models should be employed to predict trader activities and market outcomes in indefinitely lived asset markets.

2.0 GENDER DIFFERENCES IN SELF-REPORTED HEALTH STATUS: CROSS-COUNTRY EVIDENCE FROM TURKEY AND THE UNITED STATES

Co-authored with Mehmet Ali Soytas

2.1 INTRODUCTION

It is widely observed that men and women experience different health outcomes. In many countries, the life expectancy of men is shorter than that of women (Mathers et al. (2001)(86); Barford et al. (2006)(7)). According to the World Health Organization(120), the global life expectancy of women is 71 years whereas that of men is 66 years. The literature indicates gender differences in self-reported outcomes as well as in morbidity and mortality rates (Ok- suzyan et al. (2008)(95)). Moreover, it is also documented that a person' s health status is affected both by demographics and socioeconomic factors. Identifi cation and analysis of these interactions would have implications for public health policy[1]. Although females have more doctor visits and spend more on personal health care, they tend to report lower health status than men in survey data.

There are two main hypotheses regarding the social mechanisms that might account for gender differences in health outcomes. The *differential exposure* hypothesis suggests that women report lower health level than men due to higher levels of demands and obligations in their social roles and lower levels of resources to help them cope with these conditions.

[1] According to World Bank (WDI) data, public health expenditures correspond to 9.5% of GDP for U.S. and 5.1% of GDP for Turkey in 2010 (53.1% and 75.2% of total health expenditures, respectively). Moreover, there are gender differences in health expenditures. For instance, female per capita health spending is 32 % more than that of male spending in the U.S during 2004 (Cylus et al. (2011)(32)).

It follows that equivalent social role conditions and equal resources should eliminate gender differences in health. On the other hand, the *differential vulnerability* hypothesis makes reference to women's greater reactivity or responsiveness to life events and ongoing strains that are experienced in equal measure by men and women. Therefore, social roles and resources are related to health in different ways for men and women. However, neither hypothesis finds full empirical support from data. The coefficient of a gender indicator remains significant when different measures for income and household structure are taken into account in various estimations (Walters et al. (2002)(121); Denton et al. (2004)(35)). Another branch of the literature suggests that differences in the perception of health and heterogeneity in reporting behavior may lead to systematic differences in self-rated health levels. Namely, respondents may use different mapping structures between their true (objective) health levels and self-assessed health levels. Thus, two individuals with same objective health level may report different health status due to systematic differences in their thresholds (Sen (2002)(105); Jurges (2007)(68); Peracchi and Rossetti (2008)(99); Lindeboom and van Doorslaer (2004)(81); Kapteyn et al. (2007)(70)).

Understanding systematic differences in self-reported health status of sub-populations would be critical since survey data is influential in the formation of health policies for many countries[2]. However, significant attention is mostly paid to high income countries and this generates a drawback for generalizability of previous findings. In an effort to shed more light on the issue, in this study, we use cross-country survey data to investigate gender differences in self-assessed health status and determine direction of relationship between demographics, socioeconomic variables, self-reported health level and reporting thresholds. Are there gender differences in self-assessed health status? Do demographics and socioeconomic variables affect the self-rated health status and reporting thresholds? We present data from a developing country, Turkey, and a developed country, the United States. Ordered logit models are employed to quantify factors that prove important in self-reported health level. After testing for the exposure and the vulnerability hypotheses, we estimate a hierarchical ordered pro-

[2]National Center for the Health Statistics of the U.S. writes the following description for the National Health Interview Survey: "Survey results have been instrumental in providing data to track health status, health care access, and progress toward achieving national health objectives."

bit (HOPIT) to identify heterogeneity in response styles. Consistent with previous findings from other countries, the estimation results reveal a significant gender gap in self-reported health statuses for both Turkish and American respondents. Results for the relationship between demographics, socioeconomic variables and subjective health status mostly replicate previous findings. Namely, females report significantly lower subjective health statuses than males in both countries. The older the individual is, the more likely she/he will report lower self-assessed health status. The probability of reporting higher levels of health status increases with education and family income level.

We report partial evidence for both the exposure and the vulnerability hypotheses: (1) After controlling resource variables, we observe a decline in coefficients of female indicators in estimations. However, there exists a significant gender effect implying that the exposure hypothesis is not, by itself, sufficient enough to account for a gender gap in self-reported health status. (2) Tests of the vulnerability hypothesis indicate significant interaction terms for gender and some resource variables in both samples implying partial support for the vulnerability hypothesis to explain the gender differences. However, we find that the gender gap does not disappear even after controlling chronic conditions. Unlike previous findings (Case and Paxson (2005)(21); Malmusi et al. (2012)(83)), the estimation results with inclusion of chronic conditions report significant gender differences in self-reported health status for both American and Turkish individuals. Similar to the findings of Lindeboom and van Doorslaer (2004)(81) with Canadian sample, we provide evidence for significant gender effect on reporting thresholds. Finally, we note that the different labeling of the scales in surveys prevents a direct comparison between the U.S. and Turkey.

The next section discusses the related literature. Describing the data sets, Section 3 presents variables and estimation results. Section 4 concludes.

2.2 RELATED LITERATURE

Gender differences in health outcomes are well documented by previous research. The literature, mostly based on self-reported data, revealed that women have higher morbidity rates than men; whereas men have higher mortality rates (Verbrugge (1985)(117); Verbrugge and Wingard (1987)(118); Nathanson (1975)(89); Nathanson (1977)(90); Fernandez et al. (1999)(42); Oksuzyan et al. (2008)(95); Case and Paxson (2005)(21)). Inconsistency in morbidity and mortality measures is called "the gender paradox" in health related research[3]. Although women live longer on average, they do suffer from medical issues including depression, various chronic illnesses, disability and they report lower health statuses in general (Baum and Grunberg (1991)(8); McDonough and Walters (2001)(87); Verbrugge (1985)(117); Case and Paxson (2005)(21); Malmusi et al. (2012)(83); Schon and Parker (2008)(104); Crimmins et al. (2010)(29); Bourne and Brooks (2011)(13)). Moreover, some research showed that the inclusion of chronic illness measures eliminates gender differences in self-reported health status (Case and Paxson (2005) (21); Malmusi et al. (2012)(83)).

A branch of the literature reported a link between inequalities in health outcomes and socioeconomic variables such as income, education, employment and demographics (Gachter et al. 2012(48); Idler and Benyamini (1997)(66); Arber (1997)(3); Denton and Walters (1999)(34); Marmot et al. (1997)(84); Gupta et al. (2011)(54)). There is also evidence indicating a relationship between age, gender and self-reported health. For instance, Case and Deaton (2003)(20) suggested that gender differences in self-reported health lessened at older ages whereas others reported no gender difference during old age (Arber and Cooper (1999)(4); Leinonen et al. (1997)(79)). Although significant gender differences are documented by the literature, there is not a clear conclusion on the mechanisms which lead to gender differentials in health outcomes. The biological[4] and social differences between men and women are initial candidates for explaining the results. Bird and Rieker (1999)(9) discussed that social processes may create, preserve and/or increase the already existing biological sex-related health differences. Thus, health inequalities between men and women could be resulted from social conditions, biological factors or combination of both. Another line of research indicated that women tend to use more health services than men do; however, men have higher hospitalization rates. These findings may imply that women are more cautious with their health than men and tend to use health services even with minor problems whereas men could wait for the latest and serious stages of an illness (Oksuzyan et al.

[3]See Oksuzyan et al. 2010(97) and Denton et al. 2004(35) for a detailed analysis of related literature.
[4]See Oksuzyan et al. (2010)(97) an analysis of related literature.

(2010)(97)).

Considering the social factors, researchers point out two hypotheses to explain gender differences in health: the "differential exposure" hypothesis and the "differential vulnerability" hypothesis. The "differential exposure" hypothesis states that women have lower access to health-related materials and social factors enhancing health. For instance, Arber and Cooper (1999)(4) emphasized that women and men have different occupations, as well as, different income levels. Reviewing the relevant studies, Denton et al. (2004)(35) stated females report lower health levels since they face more obligations and higher demands in their social life. Although women experience more social support, they have lower levels of perceived control and self-esteem. Moreover, women are found as single parents more frequently than men and they suffer from more stress due to their marital role and gender[5]. Thus, women report lower levels of health (Denton et al. (2004)(35)).

The "differential exposure" hypothesis implies that gender inequality in health outcome is mainly based on socioeconomic factors. Once we control for socioeconomic status and available resources, there would be no gender differences in health outcomes. The "differential vulnerability" hypothesis claims that there are gender differences in reported health levels since women and men react differently to the materials and social factors that affect health. The previous research points out that women and men react to stress in different ways. Men are more sensitive to economic stressors whereas women are more likely to react social stressors. However, the evidence on the effect of stressful events on health is mixed[6] (Denton et al. (2004)(35)). Due to different reactions of men and women, health inequalities are likely to persist according to differential vulnerability hypothesis. Given that neither of two hypothesis above have full empirical support, researchers point out that differences in reporting styles may also contribute to systematic differences in self-rated health level. Dowd and Zajakova (2010)(36) stated that self-reported health measures should be used carefully since they are affected by socioeconomic conditions. People with different socioeconomic statuses may have different perceptions and expectations of health, which can easily lead to

[5]Some researchers emphasized that lifestyle of women is different than that of men. Women are less likely to smoke, consume alcohol, follow unhealthy diets, to be overweight and to be physically active (See Arber and Cooper (1999)(4); Denton et al. (2004)(35); Oksuzyan et al. (2010)(97)).

[6]See Denton et al. (2004)(35) for an analysis of related literature.

reporting heterogeneity (Dowd and Zajakova (2010)(36); Johnston et al. (2009)(67)). Sen (2002)(105) discussed that subjective perception of morbidity may be extremely misleading since it may or may not depend on social context. Studying survey data from European countries, Jurges (2007)(68) concluded that consideration of differences in response styles reduce the cross country variations in self-reported health status. Furthermore, by analyzing European data Peracchi and Rossetti (2008)(99) found that gender and regional differences in self-assessed health level are reduced by control of differences in response types. Lindeboom and van Doorslaer (2004)(81) studied Canadian surveys and reveal that reporting thresholds are significantly affected by gender and age. Using a vignettes methodology, Kapteyn et al. (2007)(70) showed that residents of the U.S. and the Netherlands use different response scales to report work disability. In the current study, we cannot provide a direct comparison across the U.S. and Turkey since survey data do not include measures of for vignettes for two countries.

Another line of literature discussed and tested the reliability of self-reported survey measures for health outcomes. Researchers show that self-reported surveys/interview data and health examination data provide similar health measures (Heliovaara et al. (1993)(59); Martikainen et al. (1999)(85)). On the other hand, some studies report different results and imply that one should be careful when interpreting survey data to make policy recommendations. Studying Mexican data, Parker et al. (2010)(98) found that obese people are likely to overreport their height and tend to underreport their weight. Authors also stated that a large part of the sample was not aware of their chronic diseases such as diabetes and hypertension (Parker et al. (2010)(98), pp. 22-23). Another study, by Baker et al. (2004)(5), discussed that self-reported measures may create large attenuation biases due to measurement errors.

2.3 DATA AND VARIABLES

We employ data from Turkish household surveys, Statistics on Income and Living Conditions (SILC), for 2006 and the U.S. National Health Interview Survey (NHIS) for 2011. The survey question for self-reported health (SRH) reads: "What is the status of your health?" Respondents choose one of the categories to reflect their health level. Thus, self-reported health status is coded as an ordinal variable and survey responses for each country is given below. We note that framing of scales are different across countries:

$$SRH_i^{Turkey} = \left\{ \begin{array}{ll} 1 & \text{if individual reports "Very bad"} \\ 2 & \text{if individual reports "Bad"} \\ 3 & \text{if individual reports "Not bad"} \\ 4 & \text{if individual reports "Good"} \\ 5 & \text{if individual reports "Very good"} \end{array} \right\}$$

$$SRH_i^{USA} = \left\{ \begin{array}{ll} 1 & \text{if individual reports "Poor"} \\ 2 & \text{if individual reports "Fair"} \\ 3 & \text{if individual reports "Good"} \\ 4 & \text{if individual reports "Very Good"} \\ 5 & \text{if individual reports "Excellent"} \end{array} \right\}$$

We have data for only certain age categories in the Turkish survey. We use a dummy variable for each age category in estimations for Turkey. We construct a dummy variable for females. Similarly, we have a dummy variable for those who are married. The unmarried category includes single, divorced, widowed and separated individuals. We also construct dummy variables for race in the U.S. data. We have data on five levels of education for Turkish respondents. "Illiterate" refers to respondents with no official education. Individuals who started primary school, but left without a diploma are included in "incomplete basic." "Primary school", "secondary school" and "high school" graduates are reflected by dummy variables in regressions. Finally, we have respondents with "tertiary" education with no further classification. For American households, we have data on years of education and we also classify education levels. "Illiterate" refers to respondents with no official education or attendants of kindergarten. Individuals who had education less than high school, i.e. less than nine years, are included in "high school (-)." "College," "associate" and "high school" graduates are reflected by dummy variables in estimations. College drop outs are represented by "college (-)." Finally, we have respondents with "tertiary" and "graduate" school education. The chronic illness dummy reflects an individual who has chronic condition(s). The own-house dummy variable is equal to one if an individual is living in a family owned house and equal to zero, otherwise. The house size measures utilized area of the house in which a respondent lives and family size indicates the number of individuals living in the household. The family income corresponds to the sum of annual income of all individuals in the same household represented in Turkish Liras and U.S. dollars. Finally, the number of children living in a household, in which the respondent also lives, is reported for both surveys.

Descriptive statistics for Turkey are provided in Table 9. In the Turkish data, we consider individuals older than age of 14 for our sample including 30,104 respondents. Females constitute 52.6% of total sample and 68.1% of respondents is married. The estimated mean age of the sample is 39.2. 41% of males and 38.1% of females completed primary school education. However, 24.4% of females are illiterate compared to 5.6% of male respondents. 50% of all respondents reported "good" health level whereas 14.9% reported "bad" health level. The average subjective health status of men is 3.62 compared to that of women at 3.42. Moreover, 30.4% of the sample reports chronic illnesses. 61.7% of males work full time whereas 55.2% of women do housework. Only 26.43% of females have a job, which is in line with labor force participation rate of women in Turkey. According to Turkish Statistical Institute, female labor force participation rate was 26% in 2006 and 30.2 % during May of 2012[7]. Thus, there is a multicollinearity problem between employment status and the female dummy since more than half of the females do housework in the Turkish sample. Moreover, many respondents are not in the labor force of the country and we include 55.05% of total sample in "not employed" category. Thus, we do not include employment level data in estimations to avoid severe multicollinearity. The average annual household income for this sample is 8,146 Turkish Liras. The mean of utilized area for an household is 99.4 m^2 and 68.9 % of all respondents live in a family-owned house. Finally, 43.1% of all respondents do not have children whereas 23.6% have only one child.

Descriptive statistics for the United States are provided in Table 10. We consider individuals older than age of 14 in our sample, which is a total of 80,766 respondents. Females constitute 52.34% of total sample and 50.27% of the sample is married. The mean age in this sample is 43.81 and 75.53% of the total sample report their race as white. 26.51% of males and 25.03% of females completed a high school level education. However, 18.61% of females

[7] http://www.turkstat.gov.tr/PreHaberBultenleri.do?id=10878

hold an associate degree compared to 17.2% of male respondents. 15.34% of the sample has a college diploma whereas 8.31% hold a graduate degree. 29.2% of all respondents reported "excellent" health condition; however, women report lower health status on average. Namely, the average health status of men is 3.76 whereas that of women is 3.68. Moreover, 14.38% of all sample report chronic illnesses. 65.73% of males are employed whereas 56.07% of women do have a job which is in line with labor force participation rates in the U.S.[8] The average annual family income for the sample is $61,860. The mean household size is 3.12 and 64.45 % of all respondents live in a family owned house. Finally, 55.88% of all respondents do not have children whereas 17.69% have only one child.

2.4 ESTIMATION RESULTS

We estimate ordered logit models for both countries to quantify the relationship between self-reported health status, demographics and socioeconomic variables. Estimated coefficients of and magnitude of the gender difference in self-reported health would not be correctly specified in an ordinary least squares regression. As one may anticipate, self-assessed health outcomes are at best ordered outcomes with no cardinal ranking. Therefore, modeling should be done via an ordered choice model. Thus, we both present ordered logit and generalized ordered logit estimations. The following equation represents our regression specification:

$SRH_i = \beta_0 + \beta X_i + \varepsilon_i$

where SRH_i is an individual's self-reported health status, β is vector of coefficients for explanatory variables, X_i is vector of socioeconomic and demographic variables for an individual and ε_i is the error term.

Table 11 and Table 12 report ordered logit results of self-reported health status for Turkey and the United States, respectively. Initial models estimate the relationship between self-rated health level, demographics and socioeconomic variables. Then, we include control variable for chronic conditions in the second specification. Finally, we add interaction terms and provide estimates to test the differential vulnerability hypothesis. For both countries,

[8] According to World Bank data, female labor force participation rate was 58% whereas male labor force participation rate was 70% in 2010. Total labor force participation rate of the U.S. was 65% in 2010.

Table 9: Descriptive Statistics for Turkey: 2006

		All		Male		Female	
		N	% Mean	N	% Mean	N	% Mean
Female		15,835	52.60				
Married*		20,514	68.14	10,077	70.62	10,437	65.91
Age							
	Ages 15-19	3,826	12.71	1,802	12.63	2,024	12.78
	Ages 20-24	3,193	10.61	1,414	9.91	1,779	11.23
	Ages 25-29	3,090	10.26	1,479	10.37	1,611	10.17
	Ages 30-34	3,124	10.38	1,447	10.35	1,647	10.4
	Ages 35-39	2,851	9.47	1,346	9.43	1,505	9.5
	Ages 40-44	2,929	9.73	1,448	10.15	1,481	9.35
	Ages 45-49	2,518	8.36	1,220	8.55	1,298	8.2
	Ages 50-54	2,209	7.34	1,114	7.81	1,095	6.92
	Ages 55-59	1,793	5.96	843	5.91	950	6
	Ages 60-64	1,415	4.7	681	4.77	734	4.64
	Ages 65+	3,156	10.48	1,445	10.13	1,711	10.81
Education							
	Illiterate	4,667	15.5	803	5.63	3,864	24.4
	Incomplete	2,520	8.37	1,048	7.34	1,472	9.30
	Primary	11,892	39.5	5,853	41.02	6,039	38.14
	Secondary	4,371	14.52	2,619	18.35	1,752	11.06
	High School	4,742	15.75	2,744	19.23	1,998	12.61
	Tertiary	1,912	6.35	1,202	8.42	710	4.48
Health Status		30,104	3.52	14,269	3.62	15,835	3.42
			(0.94)		(0.90)		(0.96)
	Very good	3,230	10.73	1,783	12.5	1,447	9.14
	Good	15,065	50.04	7,609	53.33	7,456	47.09
	Not bad	6,676	22.18	2,953	20.7	3,723	23.51
	Bad	4,500	14.95	1,662	11.65	2,838	17.92
	Very Bad	633	2.1	262	1.84	371	2.34
Chronic Illness		9,180	30.49	3,634	25.47	5,546	35.02
Employment							
	Employed	13,531	44.95	9,346	65.5	4,185	26.43
	Not Employed	16,573	55.05	4,923	34.5	11,650	73.57
Ownhouse		20,755	68.94	9,793	68.63	10,962	69.23
House Size (m^2)		30,104	99.42	14,269	99.58	15,835	99.27
			(30.53)		(30.28)		(30.75)
Family Income**		30,104	8.146	14,269	8.504	15,835	7.823
			(10.897)		(11.003)		(10.791)
# of Children		30,104	1.19	14,269	1.17	15,835	1.22
			(1.48)		(1.45)		(1.51)
	0	12,987	43.14	6,214	43.55	6,773	42.77
	1	7,121	23.65	3,398	23.81	3,723	23.51
	2+	9,996	33.21	4,657	32.64	5,339	33.62

1) * Single, widowed, divorced and other categories of marital status are coded as "unmarried."

2) ** Family income is represented in thousands of Turkish Liras.

Table 10: Descriptive Statistics for United States: 2011

		All		Male		Female	
		N	% Mean	N	% Mean	N	% Mean
Female		42,275	52.34				
Married*		40,479	50.27	20,208	52.63	20,271	48.12
Age		80,766	43.81	38,491	43.04	42,275	44.51
			(18.73)		(18.52)		(18.89)
Race							
	White	61,002	75.53	29,511	76.67	31,491	74.49
	Black	12,394	15.35	5,478	14.23	6,916	16.36
	Asian	6,113	7.57	2,869	7.45	3,244	7.67
	Other	1,257	1.56	633	1.64	624	1.48
Education**		79,383	14.22	37,813	14.14	41,570	14.30
			(3.69)		(3.73)		(3.65)
	Illiterate	470	0.59	204	0.54	266	0.64
	High School(-)	17,819	22.45	8,907	23.56	8,912	21.44
	High School	20,430	25.74	10,023	26.51	10,407	25.03
	Associate	14,239	17.94	6,504	17.20	7,735	18.61
	College(-)	7,649	9.64	3,297	8.72	4,352	10.47
	College	12,178	15.34	5,615	14.85	6,563	15.79
	Graduate	6,598	8.31	3,263	8.63	3,335	8.02
Health Status		80,766	3.72	38,491	3.76	42,275	3.68
			(1.07)		(1.07)		(1.08)
	Excellent	23,582	29.20	11,867	30.83	11,715	27.71
	Very good	24,473	30.30	11,584	30.10	12,889	30.49
	Good	22,143	27.42	10,351	26.89	11,792	27.89
	Fair	8,140	10.08	3,605	9.37	4,535	10.73
	Poor	2,428	3.01	1,084	2.82	1,344	3.18
Chronic Illness		11,566	14.38	5,187	13.53	6,379	15.16
Employment							
	Employed	49,003	60.67	25,301	65.73	23,702	56.07
	Not employed	31,763	39.33	13,190	34.27	18,573	43.93
Ownhouse		51,218	64.45	24,764	65.37	26,454	63.61
Family size		80,766	3.12	38,491	3.13	42,275	3.10
			(1.71)		(1.73)		(1.70)
Family Income***		80,766	61.86	38,491	64.11	42,275	59.81
			(48.53)		(48.81)		(48.19)
# of Children		80,766	0.86	38,491	0.83	42,275	0.89
			(1.21)		(1.20)		(1.22)
	0	45,136	55.88	22,209	57.70	22,927	54.23
	1	14,290	17.69	6,499	16.88	7,791	18.43
	2+	21,340	26.43	9,783	25.42	11,557	27.34

1) * Single, widowed, divorced and other categories in marital status and coded as "unmarried."

2) ** (-) Indicates incomplete education of the corresponding level.

3) *** Family income is represented in thousands of dollars.

we observe a significantly negative coefficient for the female dummy in regressions without interaction terms, in line with the literature. Age level coefficients are significantly negative in all regressions for both countries. The higher the age level, the lower the reported health status by Turkish and American respondents. Regression results for both data sets provide evidence on a positive correlation between self-reported health and education level. The more educated someone is, the more likely she/he is to report higher health status in Turkey and United States. However, interactions of education levels with the female dummy variable indicate different results across countries. In Turkey, there is a significant gender difference in the impact of education on self-rated health status; females are less responsive to education than males. Such differences do not exist in the United States since there are no significant interaction terms for female and education level dummies according to Table 12. Estimation results provide evidence that the self-reported health level is significantly increasing in family income of a respondent in both data sets. There is a significantly positive relationship between an individual's subjective health level and living in a family owned house. Moreover, living in a larger house is associated with reporting significantly higher health status in Turkey. Clearly, household income, owning a house and living in a larger house are all correlated with each other. Thus, we cannot make any causal inference based on ordered logit results. Estimation results report a positive relationship between self-assessed health level and the number of children in a household in the United States. A mechanism that may explain this result is the reverse causality: i.e. healthier people may have and raise more children. Moreover, results indicate that married people report significantly higher health status compared to unmarried people in Turkey whereas the United States data indicate a negative correlation. Multicollinearity between income, education, age and marriage may lead to this contrast across the two countries. The United States data indicate a consistent gap in self-reported health status across races. African-Americans and other ethnic groups except Asians report lower health status than Caucasions.

For both countries, we observe a negatively significant coefficient for the female dummy in regressions without interaction terms. This is challenging evidence for the differential exposure hypothesis since controlling for socioeconomic conditions does not completely eliminate the gender gap in self-assessed health status. Thus, we can state that the differential exposure by itself is not sufficient enough to explain gender differences in self-reported health status for Turkish and American household survey respondents. Unlike the previous literature (see Case and Paxson (2005) (21); Malmusi et al. (2012)(83)), controlling for chronic conditions do not eliminate gender differences for both countries.

One needs to be cautious about making quantitative interpretations from Tables 11 and 12 since estimated coefficients of logit models are not reporting marginal effects. We present marginal effects for the ordered logit models, controlling for chronic conditions without interaction terms, in Tables 13 and 14. We observe that females are more likely to report lower levels of health status and are less likely to report high levels of health status in both countries. Compared to the reference group, i.e., individuals in the age group of 15-19, the older the respondent is, the more likely she/he is to report lower health statuses in Turkey. The United States data also reveals significantly negative correlation between age level and subjective health status of a respondent. The probability of reporting high levels of subjective health status is increasing in education levels in both countries. However, in the United States, there is no significant difference in the self-reported health levels of respondents with less than a high school education and individuals without any official education. Individuals living in a family owned house are more likely to report higher levels of health status in both countries. Living in a larger house is associated with reporting higher self-rated health status for Turkish individuals. Being married positively impacts the probability of reporting the highest health status and negatively impacts probability of reporting the lowest health status in Turkey. Married Americans are less likely to report high subjective health status. Turkish and American respondents with higher family income levels are more likely to report higher health status. Finally, having a chronic illness has a significantly negative effect on the probability of reporting higher levels of health status for both countries. Marginal effects reported by ordered logit models provide similar results across the countries, although there are differences in magnitudes. The estimated effects of socioeconomic and demographic variables on health status are mostly consistent with previous findings in the literature. These results extend generalizability of previous findings by providing additional evidence from a developing country data and recent data from a developed country.

Table 11: Ordered Logit Estimations for Turkey

	Logit Models		
	[1]	[2]	[3]
Female	-0.265***	-0.0978***	0.427***
	[0.0239]	[0.0250]	[0.145]
Ages 20-24	-0.432***	-0.407***	-0.261***
	[0.0526]	[0.0541]	[0.0790]
Ages 25-29	-0.813***	-0.702***	-0.611***
	[0.0572]	[0.0590]	[0.0884]
Ages 30-34	-1.176***	-0.953***	-0.803***
	[0.0593]	[0.0612]	[0.0951]
Ages 35-39	-1.535***	-1.185***	-0.990***
	[0.0605]	[0.0628]	[0.0989]
Ages 40-44	-1.765***	-1.348***	-1.150***
	[0.0604]	[0.0628]	[0.0983]
Ages 45-49	-2.060***	-1.474***	-1.247***
	[0.0628]	[0.0656]	[0.103]
Ages 50-54	-2.338***	-1.586***	-1.401***
	[0.0647]	[0.0678]	[0.106]
Ages 55-59	-2.539***	-1.691***	-1.504***
	[0.0674]	[0.0708]	[0.112]
Ages 60-64	-2.695***	-1.664***	-1.385***
	[0.0710]	[0.0748]	[0.103]
Ages 65+	-3.101***	-2.020***	-1.758***
	[0.0608]	[0.06401]	[0.0659]
Incomplete	0.425***	0.418***	0.535***
	[0.0482]	[0.0503]	[0.0949]
Primary	0.713***	0.636***	0.846***
	[0.0370]	[0.0387]	[0.0797]
Secondary	0.946***	0.851***	1.100***
	[0.0506]	[0.0527]	[0.0913]
High	1.089***	0.982***	1.236***
	[0.0482]	[0.0503]	[0.0901]
Tertiary	1.541***	1.434***	1.616***
	[0.0610]	[0.0634]	[0.101]
Ownhouse	0.122***	0.0811***	0.0676*
	[0.0255]	[0.0266]	[0.0394]
House Size [m^2]	0.00336***	0.00408***	0.00438***
	[0.000396]	[0.000409]	[0.000604]
Family Income	0.0138***	0.00880***	0.0106***
	[0.00116]	[0.00118]	[0.00171]
Married	0.177***	0.174***	0.161***
	[0.0317]	[0.0331]	[0.0613]
# of Children	0.0129	0.00228	-0.0118
	[0.00861]	[0.00893]	[0.0135]
Chronic Illness		-2.731***	-2.853***
		[0.0326]	[0.0452]
Female x Ownhouse			0.0252
			[0.0536]
Female x House Size			-0.00050
			[0.000819]
Female x Family Income			-0.00325
			[0.00236]
Female x Married			0.00410
			[0.0738]

Table 11: continued			
	Logit Models		
	[1]	[2]	[3]
Female x # of Children			0.0217
			[0.0182]
Female x Chronic Illness			0.226***
			[0.0563]
Female x Ages 20-24			-0.284***
			[0.109]
Female x Ages 25-29			-0.181
			[0.120]
Female x Ages 30-34			-0.287**
			[0.126]
Female x Ages 35-39			-0.367***
			[0.129]
Female x Ages 40-44			-0.386***
			[0.129]
Female x Ages 45-49			-0.440***
			[0.134]
Female x Ages 50-54			-0.376***
			[0.139]
Female x Ages 55-59			-0.383***
			[0.145]
Female x Ages 60-64			-0.544***
			[0.153]
Female x Ages 65+			-0.491***
			[0.132]
Female x Incomplete			-0.117
			[0.113]
Female x Primary			-0.264***
			[0.0920]
Female x Secondary			-0.355***
			[0.116]
Female x High			-0.371***
			[0.111]
Female x Tertiary			-0.221
			[0.137]
cut1	-4.821***	-6.038***	-5.699***
	[0.0799]	[0.0844]	[0.121]
cut2	-2.300***	-3.235***	-2.895***
	[0.0712]	[0.0758]	[0.115]
cut3	-0.811***	-1.200***	-0.858***
	[0.0704]	[0.0732]	[0.114]
cut4	2.359***	2.339***	2.681***
	[0.0703]	[0.0729]	[0.1114]
N	30,104	30,104	30,104

1) Ages 15-19 is the reference group for age.
2) Illiterate are reference groups for age and education levels.
3) Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 12: Ordered Logit Estimations for the United States

	Ordered Logit Models		
	[1]	[2]	[3]
Female	-0.0775***	-0.0802***	-0.557***
	[0.0133]	[0.134]	[0.191]
Married	0.0179	-0.135***	-0.101***
	[0.0151]	[0.0154]	[0.0236]
Age	-0.0377***	-0.0280***	-0.0325***
	[0.000446]	[0.000461]	[0.000705]
Black	-0.260***	-0.252***	-0.165***
	[0.0189]	[0.0190]	[0.0284]
Asian	-0.0309	-0.105***	-0.0917**
	[0.0256]	[0.0258]	[0.0377]
Other Race	-0.298***	-0.281***	-0.322***
	[0.0527]	[0.0534]	[0.0757]
High School(-)	0.195**	0.0107	-0.0216
	[0.0888]	[0.0901]	[0.139]
High School	0.403***	0.224**	0.0741
	[0.0886]	[0.0899]	[0.139]
College(-)	0.573***	0.400***	0.275**
	[0.0892]	[0.0905]	[0.140]
Associate	0.648***	0.442***	0.336**
	[0.0904]	[0.0917]	[0.142]
College	0.874***	0.643***	0.528***
	[0.0898]	[0.0911]	[0.140]
Graduate	0.998***	0.753***	0.696***
	[0.0915]	[0.0927]	[0.143]
Ownhouse	0.247***	0.225***	0.197***
	[0.0157]	[0.0158]	[0.0230]
Family Size	-0.155***	-0.165***	-0.142***
	[0.00700]	[0.00710]	[0.0101]
Family Income	0.00834***	0.00728***	0.00681***
	[0.000172]	[0.000173]	[0.000247]
# of Children	0.155***	0.151***	0.137***
	[0.00959]	[0.00969]	[0.0142]
Chronic Illness		-2.076***	-2.036***
		[0.0227]	[0.0320]
			[0.186]

Table 12: continued			
	Ordered Logit Models		
	[1]	[2]	[3]
Female x Married			-0.0328
			[0.0313]
Female x Age			0.00790***
			[0.000926]
Female x Black			-0.152***
			[0.0383]
Female x Asian			-0.0358
			[0.0517]
Female x Other Race			0.0801
			[0.107]
Female x High School(-)			0.216
			[0.183]
Female x High School			0.258
			[0.182]
Female x College(-)			0.224
			[0.184]
Female x Associate			0.191
			[0.186]
Female x College			0.212
			[0.185]
Female x Graduate			0.112
			[0.188]
Female x Ownhouse			0.0468
			[0.0317]
Female x Family Size			-0.0469***
			[0.0142]
Female x Family Income			0.000899***
			[0.000344]
Female x # of Children			0.0312
			[0.0195]
Female x Chronic Illness			-0.0825**
			[0.0419]
cut1	-4.722***	-5.393***	-5.666***
	[0.0955]	[0.0977]	[0.146]
cut2	-3.020***	-3.458***	-3.729***
	[0.0938]	[0.0954]	[0.145]
cut3	-1.295***	-1.490***	-1.757***
	[0.0932]	[0.0946]	[0.144]
cut4	0.174*	0.0390	-0.226
	[0.0931]	[0.0944]	[0.144]
N	78,183	77,865	77,865

1) White is the base group for race.
2) Education reference groups is "No Education."
3) Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Family roles and how women cope with them may affect subjective assessment of health status differently for men and women. Denton and Walters (1999)(34) found that socioeconomic factors such as having a high income, working full time, caring for family are more important in predicting good health among women rather than men. In order to test the differential vulnerability hypothesis, we introduce interaction terms in the regressions. According to Tables 11 and 12, interaction terms for education and gender are significantly negative for Turkey. Thus, female and male groups have significantly different coefficients for education levels in Turkey. However, there is no significant difference in education level coefficients of males and females in the American survey. There are significant gender differences in educational attainment in Turkey, which would be the initial driving source of these results. As a developed country, the United States does not exhibit large gender differences in early education levels. Similarly, there are significant differences in coefficients for interactions of age level dummies with female dummy in both countries. Similarly, female and male populations react significantly differently to chronic conditions. Coefficients of other interaction terms such as household income, marital status, household size, house ownership and race reveal mixed results across the countries. Unlike the United States data, negative coefficients for female dummies disappear and become positive as we include interactions into the models with Turkish data. Overall, these results provide partial supporting evidence for the differential vulnerability hypothesis since women react differently to same environmental life events. However, gender differences in the self-reported health status are not fully explained by the differential vulnerability and the differential exposure hypotheses for Turkey and the U.S.

The ordered logit model assumes that the reaction of males and females to same question do not differ in their perception of health. Therefore, we need to test this assumption to receive robust findings. In this respect, we estimate a generalized ordered logit to reveal the effect of being female on different margins of reporting health status. Generalized ordered logit model (1) estimates are reported in Tables 15 and 16, with marginal effects in Tables 17 and 18. In a generalized ordered logit (1), coefficients of socioeconomic and demographic variables are allowed to differ across alternative levels of sujbective health status. This model, as it stands, is potentially inconsistent, though it can still be estimated. It provides an initial

Table 13: Marginal Effects for Turkey: Ordered Logit

Self Reported Health	Very Bad (1)	Bad (2)	Not Bad (3)	Good (4)	Very Good (5)
Probability	0.00460	0.06630	0.29766	0.58404	0.04738
Female	0.00044	0.00598	0.01631	-0.01832	-0.00442
Ages 20-24	0.00220	0.02866	0.06713	-0.08203	-0.01597
Ages 25-29	0.00432	0.05468	0.11185	-0.14593	-0.02492
Ages 30-34	0.00657	0.08075	0.14499	-0.20101	-0.03131
Ages 35-39	0.00923	0.10937	0.16912	-0.25174	-0.03599
Ages 40-44	0.01134	0.13088	0.18266	-0.28574	-0.03915
Ages 45-49	0.01346	0.15081	0.18784	-0.31159	-0.04054
Ages 50-54	0.01561	0.16985	0.18986	-0.33372	-0.04160
Ages 55-59	0.01803	0.18984	0.18784	-0.35361	-0.04210
Ages 60-64	0.01784	0.18778	0.18413	-0.34880	-0.04096
Ages 65+	0.02372	0.23577	0.20042	-0.41010	-0.04982
Incomplete	-0.00162	-0.02215	-0.06826	0.06988	0.02215
Primary	-0.00277	-0.03722	-0.10448	0.11360	0.03088
Secondary	-0.00297	-0.04095	-0.13386	0.12655	0.05123
High	-0.00335	-0.04615	-0.15241	0.14065	0.06127
Tertiary	-0.00383	-0.05576	-0.20010	0.14117	0.11653
Ownhouse	-0.00037	-0.000504	-0.01354	0.01534	0.00361
House Size [m^2]	-0.00001	-0.00025	-0.00068	0.00076	0.00018
Family Income	-0.00004	-0.00053	-0.00146	0.00165	0.00039
Married	-0.00082	-0.01093	-0.02894	0.03308	0.00762
# of Children*	-0.00001	-0.00013	-0.00038	0.00042	0.00010
Chronic Illness	0.02794	0.27737	0.28794	-0.49802	-0.09524

1) *All but the effect of number of children is significant at the 1% level

2) Ordered Logit Model [2] of Table 11 is the base for estimated effects.

Table 14: Marginal Effects for United States: Ordered Logit

Self Reported Health	Poor (1)	Fair (2)	Good (3)	Very Good (4)	Excellent (5)
Probability	0.01364	0.07375	0.31941	0.35293	0.24024
Female	0.00107	0.00530	0.01295	-0.00469	-0.01464
Married	0.00181	0.00893	0.02174	-0.00790	-0.02459
Age	0.00037	0.00185	0.00452	-0.00164	-0.00511
Black	0.00370	0.01793	0.04003	-0.01775	-0.04392
Asian	0.00147	0.00719	0.01679	-0.00679	-0.01866
Other Race	0.00432	0.02073	0.04403	-0.02148	-0.04760
High School (-)*	-0.00140	-0.00693	-0.01733	0.00584	0.01982
High School**	-0.00285	-0.01420	-0.03624	0.01137	0.04193
College (-)	-0.00478	-0.02399	-0.06486	0.01590	0.07773
Associate	-0.00503	-0.02547	-0.07160	0.01422	0.08789
College	-0.00707	-0.03587	-0.10321	0.01612	0.13004
Graduate	-0.00762	-0.03909	-0.11945	0.00839	0.15777
Ownhouse	-0.00312	-0.01529	-0.03603	0.01416	0.04028
Family Size	0.00221	0.01091	0.02659	-0.00967	-0.03004
Family Income	-0.00009	-0.00048	-0.00117	0.00042	0.00132
# of Children	-0.00202	-0.00999	-0.02435	0.00886	0.02751
Chronic Illness	0.06544	0.22974	0.16990	-0.21685	-0.24823

1) *All but the effect of high school education is significant at the 1% level. ** Significant at 5% level.

2) Ordered Logit Model [2] of Table 12 is the base for estimated effects.

insight on whether coefficients for each alternative vary or not. The inspection of estimates suggests that the coefficients differ substantially across different self-assessed health levels in both countries. A likelihood ratio test rejects the restricted model (ordered logit) at 99% critical value for both Turkey and United States[9]. Therefore, the generalized logit model mainly implies the need for taking heterogeneity in individual responses into account for the analysis. These results lead us to elaborate on reporting heterogeneity, which potentially may result in a biased support for the differential vulnerability hypothesis.

Generalized versions of ordered probit model have a structure that allows for alternative specific estimates of the latent equation (1) and the threshold parameters (2). As discussed in Greene and Hensher (2010a)(51), it is possible to estimate a more elaborate model to account for deficiencies in the generalized ordered logit model (1). Next, we report results from the generalized ordered probit model (2) where the threshold parameters are allowed to depend on individual specific observed vectors. This hypothesis about the differential response to self reported health categories outlined in the current paper is tested by using estimates from this model. Tables 19 and 20 report a model estimated via Hierarchical Ordered Probit (HOPIT) for both countries. Threshold parameters depend on the gender of the respondent in both countries and explanatory variables consist of demographics and socioeconomic conditions. If there was no heterogeneity in anticipation of thresholds, then the coefficients of the explanatory terms would be insignificant in the estimated specification. However, according to the HOPIT results, the coefficient of the female dummy variable is significant at lower health categories for Turkish respondents; a negative value for the first threshold and a positive value for the second. Thus, a Turkish individual, being female, anticipates a lower health condition when she reports SRH = 1 (very bad health) compared to that of a male Turkish individual. Moreover, "bad" health conditions (SRH = 2) reported by a female covers a much bigger range compared to that of a male in terms of underlying health status for Turkish respondents. Estimations for the United States reveal different results. The coefficient on the female dummy is significant for the highest threshold of American respondents. Namely, for the American sample, the "very good" health condition (SRH = 4) reported by a female covers a much bigger range as compared to an American

[9] Likelihood ratio tests report the following results: $LR^{USA}_{chi^2(51)} = 1768.90$ $LR^{Turkey}_{chi^2(66)} = 524.93$

Table 15: Generalized Ordered Logit Results for Turkey

Self Reported Health	Very Bad (1)	Bad (2)	Not Bad (3)	Good (4)	Very Good (5)
Female	0.475***	0.0633	-0.132***	-0.236***	
	[0.0919]	[0.0415]	[0.0335]	[0.409]	
Ages 20-24	-0.594*	-0.293**	-0.487***	-0.333***	
	[0.327]	[0.135]	[0.0858]	[0.0675]	
Ages 25-29	-0.703**	-0.553***	-0.856***	-0.505***	
	[0.329]	[0.133]	[0.0878]	[0.0791]	
Ages 30-34	-0.672**	-0.648***	-1.132***	-0.694***	
	[0.321]	[0.128]	[0.0876]	[0.0879]	
Ages 35-39	-0.607*	-0.771***	-1.315***	-1.057***	
	[0.325]	[0.127]	[0.0886]	[0.0987]	
Ages 40-44	-0.613*	-0.877***	-1.557***	-1.123***	
	[0.316]	[0.124]	[0.0882]	[0.102]	
Ages 45-49	-0.850***	-0.849***	-1.744***	-1.316***	
	[0.306]	[0.126]	[0.0914]	[0.117]	
Ages 50-54	-0.807***	-0.976***	-1.835***	-1.589***	
	[0.304]	[0.125]	[0.0946]	[0.140]	
Ages 55-59	-0.403	-1.102***	-2.023***	-1.559***	
	[0.313]	[0.126]	[0.0992]	[0.162]	
Ages 60-64	-0.294	-1.093***	-1.966***	-1.654***	
	[0.317]	[0.128]	[0.105]	[0.208]	
Ages 65+	-0.922***	-1.364***	-2.347***	-1.886***	
	[0.280]	[0.117]	[0.0934]	[0.187]	
Incomplete	0.579***	0.442***	0.291***	0.323***	
	[0.136]	[0.0666]	[0.0678]	[0.119]	
Primary	0.908***	0.760***	0.558***	0.290***	
	[0.109]	[0.0513]	[0.0511]	[0.100]	
Secondary	1.393***	1.158***	0.765***	0.420***	
	[0.239]	[0.0909]	[0.0711]	[0.107]	
High	1.565***	1.361***	0.887***	0.532***	
	[0.230]	[0.0874]	[0.0672]	[0.107]	
Tertiary	2.553***	2.061***	1.326***	0.970***	
	[0.586]	[0.148]	[0.0892]	[0.119]	
Ownhouse	-0.171	-0.0136	0.158***	0.0531	
	[0.106]	[0.0454]	[0.0354]	[0.0427]	
House Size [m^2]	0.00685***	0.00431***	0.00431***	0.00314***	
	[0.00153]	[0.00066]	[0.00056]	[0.00066]	
Family Income	0.0160**	0.0139***	0.0128***	0.00595***	
	[0.00658]	[0.00257]	[0.00184]	[0.00164]	
Married	0.650***	0.317***	0.149***	0.0119	
	[0.0951]	[0.0502]	[0.0460]	[0.0588]	
# of Children	0.0662**	-0.0108	-0.0074	0.0153	
	[0.0323]	[0.0140]	[0.0117]	[0.0149]	
Chronic Illness	-2.563***	-2.755***	-2.713***	-19.84	
	[0.139]	[0.0459]	[0.0367]	[729.4]	
Constant	4.015***	2.448***	1.401***	-1.775***	
	[0.333]	[0.135]	[0.103]	[0.130]	
N	30,104				

1) Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 16: Generalized Ordered Logit Results for United States

Self Reported Health	Poor (1)	Fair (2)	Good (3)	Very Good (4)	Excellent (5)
Female	-0.0300	-0.0595**	-0.0540***	-0.102***	
	[0.0457]	[0.0246]	[0.0162]	[0.0167]	
Married	-0.240***	-0.159***	-0.0889***	-0.102***	
	[0.0499]	[0.0272]	[0.0185]	[0.0199]	
Age	-0.0207***	-0.0272***	-0.0271***	-0.0291***	
	[0.00150]	[0.00078]	[0.00054]	[0.00061]	
Black	0.134**	-0.376***	-0.288***	-0.150***	
	[0.0574]	[0.0315]	[0.0225]	[0.0244]	
Asian	-0.0188	-0.00222	-0.153***	-0.113***	
	[0.106]	[0.0539]	[0.0313]	[0.0313]	
Other Race	-0.00571	-0.170*	-0.316***	-0.303***	
	[0.164]	[0.0899]	[0.0630]	[0.0720]	
High School (-)	0.0742	0.110	0.00269	0.0321	
	[0.177]	[0.119]	[0.109]	[0.135]	
High School	0.399**	0.356***	0.144	-0.0238	
	[0.178]	[0.119]	[0.109]	[0.135]	
College (-)	0.571***	0.552***	0.356***	0.113	
	[0.184]	[0.121]	[0.110]	[0.136]	
Associate	0.573***	0.592***	0.409***	0.157	
	[0.193]	[0.125]	[0.111]	[0.137]	
College	0.822***	0.870***	0.654***	0.359***	
	[0.196]	[0.125]	[0.111]	[0.136]	
Graduate	1.063***	0.998***	0.778***	0.488***	
	[0.225]	[0.134]	[0.113]	[0.138]	
Ownhouse	0.187***	0.333***	0.217***	0.144***	
	[0.0514]	[0.0279]	[0.0189]	[0.0199]	
Family Size	-0.223***	-0.219***	-0.208***	-0.0946***	
	[0.0245]	[0.0125]	[0.00834]	[0.00868]	
Family Income	0.0112***	0.00989***	0.00811***	0.00636***	
	[0.000861]	[0.000403]	[0.000222]	[0.000202]	
# of Children	0.238***	0.222***	0.170***	0.0949***	
	[0.0377]	[0.0183]	[0.0115]	[0.0117]	
Chronic Illness	-3.138***	-2.224***	-1.731***	-1.663***	
	[0.0613]	[0.0271]	[0.0275]	[0.0441]	
Constant	5.640***	3.357***	1.552***	0.157	
	[0.213]	[0.131]	[0.114]	[0.139]	
N	77,865	77,865	77,865	77,865	

1) Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 17: Marginal Effects for Turkey: Generalized Ordered Logit

SRH	Very Bad (1)	Bad (2)	Not Bad (3)	Good (4)	Very Good (5)
Probability	0.00588	0.06921	0.29161	0.63299	0.00029
Female	-0.00283***	-0.00156	0.03490***	-0.03043*	-0.000069
Ages 20-24	0.00444	0.01805*	0.09499***	-0.11739***	-0.000085
Ages 25-29	0.00552	0.04087***	0.16220***	-0.20848***	-0.000121
Ages 30-34	0.00520	0.05098***	0.21899***	-0.27502***	-0.000156
Ages 35-39	0.00459	0.06550***	0.24724***	-0.31713***	-0.000210
Ages 40-44	0.00464	0.07799***	0.28750***	-0.36991***	-0.000219
Ages 45-49	0.00725**	0.07264***	0.32770***	-0.40737***	-0.000238
Ages 50-54	0.00679*	0.08998***	0.32743***	-0.42395***	-0.000260
Ages 55-59	0.00282	0.11277***	0.34036***	-0.45571***	-0.000252
Ages 60-64	0.00196	0.11343***	0.32940***	-0.44455***	-0.000254
Ages 65+	0.00798**	0.14210***	0.36381***	-0.51361***	-0.000301
Incomplete	-0.00270***	-0.02363***	-0.03869***	0.06492**	0.000108
Primary	-0.00499***	-0.04504***	-0.07674***	0.12670***	0.000087
Secondary	-0.00539***	-0.05294***	-0.10310***	0.16130***	0.000143
High	-0.00593***	-0.06032***	-0.11819***	0.18426***	0.000188
Tertiary	-0.00636***	-0.06669***	-0.17006***	0.24268**	0.000448
Ownhouse	0.00097*	-0.00003	-0.03786***	0.03690***	0.000015
House Size [m^2]	-0.00004***	-0.00025***	-0.00070***	0.00100***	0.0000009
Family Income	-0.00009**	-0.00087***	-0.00199***	0.00296***	0.0000017
Married	-0.00434***	-0.01879***	-0.01172	0.03485***	0.0000034
# of Children	-0.00038**	0.00113	0.00096	-0.00172	0.0000044
Chronic Illness	0.03124***	0.29023***	0.26883***	-0.48031***	-0.109999***

1) *** p<0.01, ** p<0.05, * p<0.1

Table 18: Marginal Effects for United States: Generalized Ordered Logit

SRH	Poor (1)	Fair (2)	Good (3)	Very Good (4)	Excellent (5)
Probability	0.00709	0.06846	0.31813	0.35454	0.25175
Female	0.000211	0.00394**	0.00873**	0.00639*	-0.0193***
Married	0.00169***	0.00943***	0.0101**	-0.00193	-0.0193***
Age	0.000146***	0.00175***	0.00458***	-0.000991	-0.00549***
Black	0.000987**	0.0284***	0.0406***	-0.0425***	-0.0276***
Asian	0.000134	0.000021	0.0369***	-0.0163**	-0.0207***
Other Race	0.000040	0.0127*	0.0645***	-0.0245*	-0.0528***
High School (-)	-0.000512	-0.00698	0.00685	-0.00544	0.00608
High School	-0.00257**	-0.0206***	-0.0110	0.0386	-0.00447
College (-)	-0.00340***	-0.0300***	-0.0492**	0.0609**	0.0216
Associate	-0.00325***	-0.0307***	-0.0595***	0.0629**	0.0305
College	-0.00449***	-0.0433***	-0.0983***	0.0743***	0.0717**
Graduate	-0.00506***	-0.0448***	-0.118***	0.0673**	0.101***
Ownhouse	-0.00135***	-0.0229***	-0.0278***	0.0252***	0.0269***
Family Size	0.00157***	0.0137***	0.0343***	-0.0318***	-0.0178***
Family Income	-0.00007***	-0.000612***	-0.00124***	0.000736***	0.00120***
# of Children	-0.00167***	-0.0138***	-0.0250***	0.0226***	0.0179***
Chronic Illness	0.0903***	0.208***	0.107***	-0.180***	-0.225***

1) *** p<0.01, ** p<0.05, * p<0.1

Table 19: Hierarchical Ordered Probit Results for Turkey

	Self Reported Health	Cut 1	Cut 2	Cut 3	Cut 4
Female		-0.1554***	0.1355***	0.0306	0.0114
		[0.0402]	[0.0277]	[0.0205]	[0.0126]
Age	-0.0200***				
	[0.0006]				
Education Level	0.1378***				
	[0.0058]				
Family Income	0.0045***				
	[0.0007]				
Ownhouse	0.0625***				
	[0.0147]				
Married	0.0364**				
	[0.0158]				
# of Children	-0.0027				
	[0.0048]				
House Size	0.0024***				
	[0.0002]				
Chronic Illness	-1.5559***				
	[0.0175]				
Constant		-3.3413***	0.3359***	0.0955***	0.7120***
		[0.0508]	[0.0224]	[0.0160]	[0.0092]
N	30,104	30,104	30,104	30,104	30,104

1) Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

male in terms of underlying a "true" health status. Thus, evidence from both countries indicates that reporting thresholds for subjective health statuses are significantly different across genders.

2.5 CONCLUSION

Frequently documented gender differences in health outcomes are thought to arise from biological factors, socioeconomic factors and probably from the interaction of both. Most studies reporting results from North America and Europe neglect developing countries. In an effort to fill this gap and test the generalizability of previous findings, we present health survey data from a developing country, Turkey, as well as from a developed country, the United States. We extend the literature by introducing evidence from a cross-country data set to analyze determinants of gender differences in self-assessed health status. However, differences in the framing of the scales of survey questions prevent a direct comparison of

Table 20: Hierarchical Ordered Probit Results for United States

	Self Reported Health	Cut 1	Cut 2	Cut 3	Cut 4
Female		0.0019	0.0322	-0.0057	0.0348***
		[0.0221]	[0.0209]	[0.0119]	[0.0112]
Married	-0.1092***				
	[0.0088]				
Age	-0.0150***				
	[0.0003]				
Education Level	0.0367***				
	[0.0012]				
Black	-0.1595***				
	[0.0111]				
Asian	-0.0745***				
	[0.0151]				
Other Race	-0.1849***				
	[0.0311]				
Ownhouse	0.0954***				
	[0.0092]				
Family Income	0.0041***				
	[0.0001]				
# of Children	-0.0058				
	[0.0036]				
Chronic Illness	-1.1640***				
	[0.0123]				
Constant		-2.4807***	0.0192	0.1093***	-0.1042***
		[0.0259]	[0.0158]	[0.0088]	[0.0082]
N	77,865	77,865	77,865	77,865	77,865

1) Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

results across countries.

This study provides tests of alternative explanations for the gender gap in self-rated health status: 1) the "differential exposure" hypothesis, 2) the "differential vulnerability" hypothesis, 3) heterogeneity in reporting thresholds. We estimate ordered choice models to quantify social factors that prove important in self-reported health outcomes. Results indicate significant gender differences in self-reported health levels. The direction of the relationship between socioeconomic status indicators and self-assessed health statuses are mostly consistent with the literature. However, unlike previous results, we find significant gender differences even with the controls of chronic illnesses. We also report that the differential vulnerability and the differential exposure hypotheses can partially explain gender differences in self-assessed health outcomes but they are not sufficient to account for a full explanation of the gap. Thus, there remains a significant gender gap in self-rated health status, which is not explained by chronic illness conditions or social factors. Moreover, by employing a generalized ordered logit model and a hierarchical ordered probit model, we show that reporting cut-offs for subjective health status significantly varies across genders.

Results of the current study provide additional evidence that males and females report significantly different subjective health levels. Our findings suggest that the gender gap is driven by additional mechanisms other than "differential exposure," "differential vulnerability" and chronic conditions. One such factor is the reporting differences between men and women in both countries. Heterogeneity in anticipation of a current objective health may lead to different values attached to objective health outcomes. Namely, both Turkish and American females use different thresholds than their male counterparts in reporting their subjective health status. Moreover, there are cross-country differences in female reporting behavior. While Turkish females use a larger range for reporting SRH=2, American females have a higher cut-off point for reporting SRH=4. Reporting heterogeneity in thresholds leads us to further investigate the issue, possibly, with a theoretical model. Thus, a further analysis of gender differences in self-assessed health status is necessary to identify all accounting factors of the gap. In a complementary study, we propose a theoretical model to explain gender differences in self-reported health status and hypothesize that the gender gap in health status is driven also by heterogeneity in individual discount rates.

3.0 DOES HETEROGENEITY IN INDIVIDUAL DISCOUNT RATES EXPLAIN THE GENDER GAP IN SELF-ASSESSED HEALTH STATUS?

Co-authored with Mehmet Ali Soytas

3.1 INTRODUCTION

Health outcomes significantly differ across genders. The literature frequently documents that females report significantly worse self-assessed health statuses than males. Subjective health statuses of survey respondents vary across socioeconomic conditions such as income, education, race, age, etc. Gender differences may arise from biological factors, socioeconomic conditions or the interactions of both. A significant gender gap in subjective health status exists when different measures for demographics, socioeconomic variables and social mechanisms are taken into account (Walters et al. (2002)(121); Denton et al. (2004)(35); Soytas and Kose (2013)(110)). Soytas and Kose (2013)(110) indicated that there is still a significant gender gap in self-reported health statuses even after controlling for chronic illness conditions unlike in previous studies (Case and Paxson (2005)(21); Malmusi et al. (2012)(83)). Moreover, there is evidence of reporting heterogeneity in self-assessed health statuses. Lindeboom and van Doorslaer (2004)(81) showed that reporting thresholds of Canadian respondents are significantly affected by gender and age whereas Soytas and Kose (2013)(110) reported that Turkish and American females use different reporting cutoffs than their male counterparts.

Although the previous literature offers some explanations, there still remains a significant and unexplained gender gap in self-reported health statuses. Denton et al. (2004)(35) asserted that models covering more health-related variables and a detailed investigation of the gender differences in health would be valuable. In an effort to fill this gap in the literature and provide a more robust mechanism to explain the gender gap in self-reported health, we present a theoretical model. In most health surveys, participants are asked to evaluate their health on a 1-5 grade scale. The respondents' assessment of their health levels are anticipated as a discrete measure, which is a proxy for their true health statuses. However, this measure does not have to reflect the current well-being of an individual. From the economist's point of view, we consider self-reported health status levels as a proxy for the respondents' perception of the total utility derived from their health, which contains both current and expected future health levels. We suggest that the current utility associated with the current health state is the solution to a dynamic problem, which includes the discounted sums of future utilities. This approach, theoretically, can produce different current valuation functions for two individuals, who even may have the same level of unobserved true health today. Therefore, a male and a female may actually report different discrete health statuses depending on their valuation of the future, even if they have the same current objective, unobserved true health.

We hypothesize that heterogeneity in individual discount rates would lead to reporting heterogeneity in self-assessed health status. Then, the gender differences in the valuation of the future will help with explaining the gender gap in subjective health statuses. There is evidence on gender differences in subjective individual discount rates. Silverman (2003)(106) concluded that women discount future rewards less than men. Similarly, Zimbardo et al. (1997)(126) found that females are more future-oriented than males whereas men are more present-oriented. Gender differences in subjective discount rates could crucially affect self-reported health levels of individuals. Thus, we propose a dynamic theoretical model to explain the gender differences in self-reported health statuses and suggest that the gender gap is driven also by heterogeneity in discount rates of future utility.

We use some data from the U.S. National Health Interview Survey of 2012 to test the predictions of our model and theoretical identification. Following the previous literature, we employ smoking habits as proxies for individual discount rates (Fuchs (1982)(47); Scharff and Viscusi (2011)(103); Peretti-Watel et al. (2013)(100)). We estimate the identification parameters implied by the dynamic model and compare them with an ordered probit estimation. Results indicate magnitude differences across coefficients of the ordered probit and the structural model identification. We conclude that accounting for heterogeneity in individual discount factors explains a substantial portion of the gender gap in self-assessed health statuses. Thus, attempts to explain the gender gap in self-rated health statuses and policy makers should take heterogeneity in individual discount rates into account.

Section two provides a brief discussion of the related literature. The third section describes theoretical models and identification equations. Following the data description, section five explains the estimation and results to highlight empirical outcomes that can fit into observed trend in the data. Section six concludes.

3.2 RELATED LITEATURE

Research, mostly based on survey data, revealed gender differences in health outcomes. There is a huge literature devoted to an explanation of the gender gap in subjective health status. Biological factors, socioeconomic variables and demographics are frequently stated as explanatory variables of the gap. Providing a review of the literature, Soytas and Kose (2013)(110) showed that accounting for socioeconomic variables, demographics and chronic conditions are not sufficient to explain gender differences in self-assessed health statuses. Using data sets from the United States and Turkey, the authors present evidence on gender differences in reporting behavior and concluded that reporting thresholds are affected by the gender of the respondent in both countries. We need to investigate the underlying mechanisms for gender differences in subjective assessments of health levels. This study considers another factor: the subjective discount rate[1], which may significantly affect the behavior of individuals. Thus, we provide a review of studies on discounting factor and health-related variables in this section.

Researchers showed that agents generally discount the value of a future rewards (consumption, income, etc.) relative to the value of immediate rewards. There are many terms, such as *time preference, positive rate of intertemporal substitution and delay discounting*, to refer to this phenomenon (Chao et al. (2009) (23)). The degree of discounting the future

[1] We follow this term used by Chao et al. (2009) (23).

may change across individuals depending on demographics and social factors[2]. For instance, Coller and Williams (1999)(28) showed that individual discount rates are affected by socioeconomic characteristics and male participants have significantly higher discount rates. Moreover, researchers analyzed the relationship between discount rates, age, race, education, income, household size, religious beliefs, the number of dependents, smoking, etc. (See Lawrence (1991)(75); Coller and Williams (1999)(28); Carter et al. (2012)(19); Chabris et al. (2008)(22); Harrison et al. (2002)(55); Eckel et al. (2005)(38); Waner and Pleeter (2001)(122)).

The literature provides mixed evidence on gender differences in subjective individual discount rates[3]. Similar to Coller and Williams (1999)(28), Kirby and Marakovic (1996)(73) reported higher discount rates for males. Moreover, Silverman (2003)(106) provided a meta-analysis of 33 studies and stated that women discount future rewards less than men. However, the author noted that gender differences are small and dependent on measurement type. Zimbardo et al. (1997)(126) stated that females are more future-oriented than males whereas men are more present-oriented. In contrast, studying a Netherlands sample, Van Praag and Booij (2003)(116) revealed that women have higher discount rates than men. On the other hand, Harrison et al. (2002)(55) estimated identical discount rates for men and women whereas these rates are sensitive to sociodemographic variables such as age, income, education and employment status. Warner and Pleeter (2001)(122) found no gender differences in discount rates of men and women by using a military personnel data.

Some studies discovered that smoking habits are correlated with individual discount rates (Fuchs (1982)(47); Scharff and Viscusi (2011)(103); Peretti-Watel et al. (2013)(100)). Many studies used smoking behavior as a proxy of individual discount factors. Considering smoking habits as a predictor of discount factors, some researchers used smoking habits as an instrument for education and labor market choices (see Evans and Montgomery (1994)(39); Chevalier and Walker (2001)(26); Fersterer and Winter-Ebmer (2003)(43); Munasinghe and Sicherman (2000)(88)). Providing a review of empirical studies on education and health, Grossman (2006)(64) discussed the potential of time preferences as an omitted variable to

[2] Frederick et al. (2002)(45) gave a more extensive overview of the findings on time discounting.

[3] Teuscher and Mitchell (2011)(113) provided an excellent review of studies on delay discounting.

explain health outcomes. For instance, Fuchs (1982)(47) reported a negative, although not significant, relationship between subjective health statuses and discount factors of the individuals. Moreover, Van Der Pol (2011)(115) showed that controlling time preferences reduces the effect of education on self-assessed health statuses of Dutch populations. The author reported a negatively-significant coefficient for a time preference measure. Moreover, Chao et al. (2009)(23) provided evidence for the relationship between health measures and subjective discount rates. The authors documented that physical health and survival probability has a U-shaped relationship with subjective discount rates. Namely, individuals with very bad and very good health levels have higher discount rates. Some studies indicated that individuals with higher rates of time preference (and lower risk aversion (Ida and Odo (2009)(65)) are more likely to smoke (Ida and Odo (2009)(65); Scharff and Viscusi (2011)(103))), whereas Khwaja et al. (2007)(71) exihibited no significant relationship between smoking and subjective measures of time preference. Harrison et al. 2010(56) observed heterogeneity in the discount rates of male smokers and non-smokers while the discount rates do not significantly differ in female populations. Leonard et al. (2013)(80) found that higher tolerance of risk and more patience in time preferences are significantly correlated with higher stages of physical activity in a low income African-American community. Obtaining flu shots, drinking behavior, BMI differences in a specific year are also employed as proxies for individual discount rates (Chapman and Coups (1999)(24); Borghans and Golsteyn (2006)(10); Vuchinich (1998)(119)). Finally, Lawless et al. (2013)(76) provided a review of the relationship between time preferences and health behaviours. The authors discussed the interaction between time preferences and health concerns such as smoking and obesity. They indicated that empirical studies measure time preferences with proxy variables such as saving rates, credit card debt, personal savings, (lagged) debt to income ratios. Given the results from previous studies, we hypothesize that gender differences in subjective discount rates/time preferences could crucially affect self-reported health levels of individuals. Thus, we use smoking behavior as a proxy for individual discount factors in this study.

3.3 MODEL

Individuals derive utility from their health statuses and they respond to the changes in their life-cyle health through a discount rate. Namely, an individual calculates his/her current value of health as a sum of current and discounted future health benefits. In this context, we set up the current value of an individual's health as follows:

$$V(x_{it}) = u(x_{it}) + E_t \left\{ \sum_{s=t+1}^{T} \beta_i^{s-t} u(x_{is}) \right\} \tag{3.1}$$

where x_{it} is the vector of observed characteristics of the individual, $u(x_{it})$ is the utility function and β_i is discount factor of the individual. Next, we make assumptions on the functional form of the utility, which depends on observable individual characteristics.

Assumption 1 Suppose we have a linear health utility function of the following form where γ is the vector marginal utility coefficients for observed characteristics and ε_{it} unboserved component of utility:

$$u(x_{it}) = \gamma' x_{it} + \varepsilon_{it} \tag{3.2}$$

Assumption 2 Suppose the unobserved component of the utility is independent across the individuals and over time with a mean of zero. Thus, we have the followings:

$$1)\ E[\varepsilon_{it}] = 0, \quad 2)\ E[\varepsilon_{it}|x_{it}] = 0, \quad 3)\ E[\varepsilon_{it}\varepsilon_{i't}] = 0, \quad 4)\ E[\varepsilon_{it}\varepsilon_{is}] = 0$$

Assumption 3 Suppose x_{it} vector has four elements, a constant, education (x_1), income (x_2) and age (x_3), which affect the health benefits.

Using the linear utility function and replacing it into (3.1), we get:

$$V(x_{it}) = \gamma' x_{it} + \varepsilon_{it} + E_t \left\{ \sum_{s=t+1}^{T} \beta_i^{s-t} \left(\gamma' x_{is} + \varepsilon_{is}\right) \right\}$$

Then, by assumptions 2 and 3, we write:

$$\begin{aligned} V(x_{it}) &= \gamma_0 + \gamma_1 x_{1i} + \gamma_2 x_{2it} + \gamma_3 x_{3it} + \varepsilon_{it} \\ &\quad + E_t \left\{ \sum_{s=t+1}^{T} \beta_i^{s-t} \left[\gamma_0 + \gamma_1 x_{1it} + \gamma_2 x_{2is} + \gamma_3 x_{3is} + \varepsilon_{is}\right] \right\} \end{aligned}$$

Assumption 4 For the sake of derivation, we assume an infinite time horizon: i.e. $T = \infty$.

We note that this assumption is not critical for the validity of the results. Moreover, for any future time s, age of an individual is written as follows: $x_{3is}= x_{3it}+s-t$. Then, the value function of an indvidual is expressed as follows:

$$\begin{aligned} V(x_{it}) &= \gamma_0+\gamma_1 x_{1i}+\gamma_2 x_{2it}+\gamma_3 x_{3it}+\varepsilon_{it} \\ &\quad +\gamma_0\sum_{s=t+1}^{\infty}\beta_i^{s-t}+\left(\gamma_1\sum_{s=t+1}^{\infty}\beta_i^{s-t}\right)E_t\{x_{1i}\}+\gamma_2 E_t\left\{\sum_{s=t+1}^{\infty}\beta_i^{s-t}x_{2is}\right\} \\ &\quad +\gamma_3 E_t\left\{\sum_{s=t+1}^{\infty}\beta_i^{s-t}(x_{3it}+s-t)\right\}+E_t\left\{\sum_{s=t+1}^{\infty}\beta_i^{s-t}\varepsilon_{is}\right\} \end{aligned}$$

We simplify the above expression by using the following facts: $\sum_{s=t+1}^{\infty}\beta_i^{s-t}=\frac{\beta_i}{1-\beta_i}$,

$\sum_{s=t+1}^{T}\beta_i^{s-t}(s-t)=\frac{\beta_i}{(1-\beta_i)^2}$.

Defining $\rho_i=\frac{\beta_i}{1-\beta_i}$ and using $E_t\{x_{1i}\}=x_{1i}$, $E_t\{x_{3it}\}=x_{3it}$, we write:

$$\begin{aligned} V(x_{it}) &= \gamma_0+\gamma_1 x_{1i}+\gamma_2 x_{2it}+\gamma_3 x_{3it}+\varepsilon_{it} \\ &\quad +\gamma_0\rho_i+\gamma_1\rho_i x_{1i}+\gamma_2 E_t\left\{\sum_{s=t+1}^{\infty}\beta_i^{s-t}x_{2is}\right\} \\ &\quad +\gamma_3\rho_i x_{3it}+\gamma_3\rho_i(1+\rho_i)+\sum_{s=t+1}^{\infty}\beta_i^{s-t}E_t\{\varepsilon_{is}\} \end{aligned}$$

Finally, the last expression is equal to 0 by assumption 2.

$$\begin{aligned} V(x_{it}) &= \gamma_0+\gamma_1 x_{1i}+\gamma_2 x_{2it}+\gamma_3 x_{3it}+\varepsilon_{it}+\gamma_0\rho_i+\gamma_1\rho_i x_{1i}+ \\ &\quad \gamma_2 E_t\left\{\sum_{s=t+1}^{\infty}\beta_i^{s-t}x_{2is}\right\}+\gamma_3\rho_i x_{3it}+\gamma_3\rho_i(1+\rho_i) \end{aligned}$$

We follow Zabalza (1979)(125) for the evolution of an individual's income.

Assumption 5 Suppose that the future income of an individual depends on the current income and the future income has the following trajectory: $x_{2is}= x_{2it}(1+\lambda(s-t))$, where λ is the annual growth in real income over years.

We plug this income trajectory into the valuation function and write:

$$\begin{aligned} V(x_{it}) &= \gamma_0+\gamma_1 x_{1i}+\gamma_2 x_{2it}+\gamma_3 x_{3it}+\varepsilon_{it}+\gamma_0\rho_i+\gamma_1\rho_i x_{1i} \\ &\quad +\gamma_2 E_t\left\{\sum_{s=t+1}^{\infty}\beta_i^{s-t}(x_{2it}(1+\lambda(s-t)))\right\}+\gamma_3\rho_i x_{3it}+\gamma_3\rho_i(1+\rho_i) \end{aligned}$$

Using $E_t\{x_{2it}\}=x_{2it}$, we have:

$$V(x_{it}) = (\gamma_0+\gamma_3\rho_i)(1+\rho_i)+\gamma_1(1+\rho_i)x_{1i}+\gamma_2(1+\rho_i)(1+\lambda\rho_i)x_{2it}+\gamma_3(1+\rho_i)x_{3it}+\varepsilon_{it} \tag{3.3}$$

The estimation model identifies parameters for the value function:

$$V(x_{it})=\alpha_0+\alpha_1 x_{1i}+\alpha_2 x_{2it}+\alpha_3 x_{3it}+\varepsilon_{it} \tag{3.4}$$

where $\alpha_0=(\gamma_0+\gamma_3\rho_i)(1+\rho_i)$, $\alpha_1=\gamma_1(1+\rho_i)$, $\alpha_2=\gamma_2(1+\rho_i)(1+\lambda\rho_i)$ and $\alpha_3=\gamma_3(1+\rho_i)$.

Since we can observe education, income and the age of an individual from a given survey sample, the estimation of the model requires direct measures of health valuations given in (3.4). However, in most data sets, we only observe self-assessed health outcomes rather than a continuous measure for health benefits/levels. Therefore, in order to make the model in (3.1) operational, we need to define an unobserved component, which takes the differences in self-assessed health (SAH) outcomes into account.

The health benefits of an individual cannot be observed. However, as a function of health benefits, self-assessed health statuses are observed as a discrete variable. We define the relationship of the valuation function with discretely reported SAH categories as follows:

$$SAH_i=\left\{\begin{array}{ccc} 1 & if & -\infty<V(x_{it})\leq c_1 \\ 2 & if & c_1<V(x_{it})\leq c_2 \\ 3 & if & c_2<V(x_{it})\leq c_3 \\ 4 & if & c_3<V(x_{it})\leq c_4 \\ 5 & if & c_4<V(x_{it})\leq \infty \end{array}\right\}$$

Unlike general models using SAH measure, we hypothesize that SAH reflects not only current health but also life-time health benefits. In fact, the two are not separable in an economic context. Having the SAH measure as an indicator for the current health, most models accumulate the effects of life-cycle expectations into an unobserved component. The performance of SAH, in this framework, depends on empirical assumptions on an unobserved error term of the model. This assumption determines the estimation model type used in the literature. For instance, a normally distributed error term will lead to an ordered probit whereas a logistic distribution assumption will drive an ordered logit model. In most cases, the distributional assumption is the only way to assign a latent health to discrete SAH outcomes. There is no direct method to test the validity of current health versus the expectations augmented version considered in this paper. The error term mainly serves to match latent continuous variable (health or expected discounted health, or anything else) to discrete SAH categories. There is no theoretical framework to link what individuals really report as SAH and explanations for their incentives to do so. If their current health is reported as SAH, how do they anticipate it? From an empirical point of view, one may speculate that reported current health may reflect the result of an individual's criteria to judge his/her current health conditions. Therefore, in this context, SAH still may be considered as the current health; however, it may be a solution to a life-cyle problem for the individual. In this paper, we address this problem and shed some light on the validity of augmenting expectations in modelling for self-assessed health statuses.

If we assume that the current health benefit is H^*, which is a function of the current observed variables and an independent and identically distributed unobserved error term, we would write:

$$H^* = u(x_{it}) + \varepsilon_{it} \tag{3.5}$$

Then depending on the assumption on the distribution of unobserved factor ε_{it}, the model is an ordered logit or an ordered probit model with threshold parameters $c_i,\ i = 1, ..4$. This kind of a model can be estimated with a maximum likelihood method. However, the above representation of the problem includes not only the current considerations but also the effect on life-cycle slope of the current health status. If the correct model is the health benefits model in equation (3.1) rather than the current health model in equation (3.5), then these models will explain different structural effects even there is an identical observed outcome.

We observe that the estimation equation (3.4) can only identify $(\alpha_1, \alpha_2, \alpha_3)$. In order to obtain underlying utility parameters $(\gamma_0, \gamma_1, \gamma_2, \gamma_3)$, more assumptions are needed. We allow a specific form of individual heterogeneity to identify the utility parameters. We have an individual specific discount factor variable defined as follows:

$$\rho_i = \frac{\beta_i}{1-\beta_i}$$

We use ρ_i as a proxy for the subjective discount factor of an individual: i. Replacing the corresponding terms in the estimation equation for the heterogeneity in individual subjective discounting, we obtain:

$$V(x_{it}) = (\gamma_0 + \gamma_3\rho_i)(1+\rho_i) + \gamma_1(1+\rho_i)x_{1i} + \gamma_2(1+\rho_i)(1+\lambda\rho_i)x_{2it} + \gamma_3(1+\rho_i)x_{3it} + \varepsilon_{it}$$

Rearranging and collecting for similar terms, we write:

$$\begin{aligned} V(x_{it}) &= \gamma_0 + \gamma_0\rho_i + \gamma_3\rho_i^2 + \gamma_1(x_{1i} + \rho_i x_{1i}) + \gamma_2(x_{2i} + \rho_i x_{2it}) \\ &\quad + \lambda\gamma_2(\rho_i x_{2it} + \rho_i^2 x_{2it}) + \gamma_3(x_{3i} + \rho_i x_{3it}) + \varepsilon_{it} \end{aligned} \tag{3.6}$$

The above estimation equation identifies all the utility parameters including the coefficient of income growth, λ.

3.3.1 Accounting for Individual Subjective Discount Rates

The theoretical model with heterogeneity in individual discount factors enables us identify the utility parameters. Since discount rates are shown to vary significantly with respect to socioeconomic conditions and demographics, we make an assumption on the functional form of the relationship between individual discount rates and socioeconomic variables.

Assumption 6 Suppose that indiviual discount rates in our model is in the following linear form:

$$\rho_i = \theta' w_i + u_i \tag{3.7}$$

where θ is a $L \times 1$ parameter vector and w_i is a $L \times 1$ vector of containing socioeconomic variables for an individual i. A naive estimation will take the predicted values $\hat{\rho}_i$ from equation (3.7) and replace them into (3.6) to estimate the coefficients γ. Moreover, we need to correct for calculation of standard errors in the first stage estimation.

The main hypothesis of this paper states that the coefficients, γ, identified in this framework are significantly different from the coefficients identified without future looking structure. In the latter case, the coefficients we can identify are $\{\alpha_1, \alpha_2, \alpha_3\}$. An essential contribution of this paper is the inclusion of stochastic individual specific discount rate. Even if coefficients of vector θ turn out to be insignificant in equation (3.7), the existence of stochastic discounting can lead to partial identification of the coefficients. This paper addresses these identification issues and the implications of assuming a discount function instead of a fixed discount rate. We use theoretical results to show that the gender gap in self-rated health statuses, a puzzle in the health economics literature, can be explained by taking the differences in stochastic discounting into account.

3.3.2 A Simple Model

In order to evaluate the identification power of the structural model, let's assume a simpler model with only education.

$$V(x_{it}) = \gamma_0 + \gamma_1 x_{1i} + \varepsilon_{it} + \gamma_0 \rho_i + \gamma_1 \rho_i x_{1i}$$

Replacing for ρ_i and using the linear functional form assumption, we write:

$$\begin{aligned}
V(x_{it}) &= \gamma_0(1 + \rho_i) + \gamma_1(x_{1i} + \rho_i x_{1i}) + \varepsilon_{it} \\
V(x_{it}) &= \gamma_0(1 + \theta' w_i + u_i) + \gamma_1(x_{1i} + (\theta' w_i + u_i) x_{1i}) + \varepsilon_{it} \\
V(x_{it}) &= \gamma_0 + \gamma_0 \theta' w_i + \gamma_1 x_{1i} + \gamma_1 \theta' w_i x_{1i} + (\gamma_0 u_i + \gamma_1 u_i x_{1i} + \varepsilon_{it})
\end{aligned}$$

Estimating this model is a difficult task since health level measures are not continouous. The SAH score of an individual allows us to write the model as follows:

$$H = \left\{ \begin{array}{lll} 1 & if & \gamma_0 + \gamma_0\theta' w_i + \gamma_1 x_{1i} + \gamma_1\theta' w_i x_{1i} + (\gamma_0 u_i + \gamma_1 u_i x_{1i} + \varepsilon_{it}) \leq c_1 \\ 2 & if & c_1 < \gamma_0 + \gamma_0\theta' w_i + \gamma_1 x_{1i} + \gamma_1\theta' w_i x_{1i} + (\gamma_0 u_i + \gamma_1 u_i x_{1i} + \varepsilon_{it}) \leq c_2 \\ 3 & if & c_2 < \gamma_0 + \gamma_0\theta' w_i + \gamma_1 x_{1i} + \gamma_1\theta' w_i x_{1i} + (\gamma_0 u_i + \gamma_1 u_i x_{1i} + \varepsilon_{it}) \leq c_3 \\ 4 & if & c_3 < \gamma_0 + \gamma_0\theta' w_i + \gamma_1 x_{1i} + \gamma_1\theta' w_i x_{1i} + (\gamma_0 u_i + \gamma_1 u_i x_{1i} + \varepsilon_{it}) \leq c_4 \\ 5 & if & c_4 < \gamma_0 + \gamma_0\theta' w_i + \gamma_1 x_{1i} + \gamma_1\theta' w_i x_{1i} + (\gamma_0 u_i + \gamma_1 u_i x_{1i} + \varepsilon_{it}) \end{array} \right\}$$

Rewriting the expression just for the 1st and 2nd line, we get:

$$H = \left\{ \begin{array}{l} 1 \quad if \quad \gamma_0 u_i + \gamma_1 u_i x_{1i} + \varepsilon_{it} \leq c_1 - [\gamma_0 + \gamma_0\theta' w_i + \gamma_1 x_{1i} + \gamma_1\theta' w_i x_{1i}] \\ 2 \; if \; c_1 - [\gamma_0 + \gamma_0\theta' w_i + \gamma_1 x_{1i} + \gamma_1\theta' w_i x_{1i}] < \gamma_0 u_i + \gamma_1 u_i x_{1i} + \varepsilon_{it} \leq c_2 - [\gamma_0 + \gamma_0\theta' w_i + \gamma_1 x_{1i} + \gamma_1\theta' w_i x_{1i}] \end{array} \right\}$$

We arrange terms and obtain:

$$H = \left\{ \begin{array}{l} 1 \quad if \quad (\gamma_0 + \gamma_1 x_{1i}) u_i + \varepsilon_{it} \leq [c_1 - \gamma_0 - \gamma_0\theta' w_i - \gamma_1 x_{1i} - \gamma_1\theta' w_i x_{1i}] \\ 2 \; if \; [c_1 - \gamma_0 - \gamma_0\theta' w_i - \gamma_1 x_{1i} - \gamma_1\theta' w_i x_{1i}] < (\gamma_0 + \gamma_1 x_{1i}) u_i + \varepsilon_{it} \leq [c_2 - \gamma_0 - \gamma_0\theta' w_i - \gamma_1 x_{1i} - \gamma_1\theta' w_i x_{1i}] \end{array} \right\}$$

Assumption 7 We assume that u_i and ε_{it} are both normally distributed as $N(0, \sigma_u^2)$ and $N(0, \sigma_\varepsilon^2)$.

Assumption 8 We assume that the correlation between the unobserved components is κ.

This model will have the same structure as an ordered probit model, which allows heteroscedasticity in variance of the unobserved component. Therefore, the coefficients are identified (Greene and Hensher (2010a)(51)). Yet, identification of all parameters of the model requires at least one shifter; a variable that affects the subjective discount rate, but not the subjective health outcome. The candidate variable for the shifter is identified by many studies in the literature of subjective discounting. The commonly used variable in this literature, possibly due to vast availability in the main data sets, is the smoking habit of an individual. This variable has a strong positive correlation with risk-taking and time-discounting behavior as discussed above. Clearly, smoking will be an endogenous variable since it is expected that individuals who smoke would have relatively lower health status. That would be a serious problem in a linear regression based setting; however, it can be endogenized in our model by taking the correlation between ε_{it} and u_i into account. Namely, unobserved factors affecting an individual's discount factor (u_i) will be correlated with unobserved factors affecting an individual's life-time utility from health (ε_{it}). Thus, our empirical strategy will account estimating the correlation parameter, κ.

$$\begin{aligned}
P(H=1) &= \Phi\left(\frac{[c_1-\gamma_0-\gamma_0\theta' w_i-\gamma_1 x_{1i}-\gamma_1\theta' w_i x_{1i}]}{\sqrt{(\gamma_0+\gamma_1 x_{1i})^2\sigma_u^2+\sigma_\varepsilon^2+2\kappa_{u,\varepsilon}(\gamma_0+\gamma_1 x_{1i})\sigma_u\sigma_\varepsilon}}\right)\\
P(H=2) &= \Phi\left(\frac{[c_2-\gamma_0-\gamma_0\theta' w_i-\gamma_1 x_{1i}-\gamma_1\theta' w_i x_{1i}]}{\sqrt{(\gamma_0+\gamma_1 x_{1i})^2\sigma_u^2+\sigma_\varepsilon^2+2\kappa_{u,\varepsilon}(\gamma_0+\gamma_1 x_{1i})\sigma_u\sigma_\varepsilon}}\right)-\Phi\left(\frac{[c_1-\gamma_0-\gamma_0\theta' w_i-\gamma_1 x_{1i}-\gamma_1\theta' w_i x_{1i}]}{\sqrt{(\gamma_0+\gamma_1 x_{1i})^2\sigma_u^2+\sigma_\varepsilon^2+2\kappa_{u,\varepsilon}(\gamma_0+\gamma_1 x_{1i})\sigma_u\sigma_\varepsilon}}\right)
\end{aligned}$$

Assumption 9 We assume that the variance of the unobserved factor ε is 1: $\sigma_\varepsilon^2 = 1$.

Under assumptions 8 and 9, the model is characterized by the following equations:

$$\begin{aligned}
P(H=1) &= \Phi\left(\frac{[c_1-\gamma_0-\gamma_0\theta' w_i-\gamma_1 x_{1i}-\gamma_1\theta' w_i x_{1i}]}{\sqrt{(\gamma_0+\gamma_1 x_{1i})^2\sigma_u^2+1+2\kappa_{u,\varepsilon}(\gamma_0+\gamma_1 x_{1i})\sigma_u}}\right)\\
P(H=2) &= \Phi\left(\frac{[c_2-\gamma_0-\gamma_0\theta' w_i-\gamma_1 x_{1i}-\gamma_1\theta' w_i x_{1i}]}{\sqrt{(\gamma_0+\gamma_1 x_{1i})^2\sigma_u^2+1+2\kappa_{u,\varepsilon}(\gamma_0+\gamma_1 x_{1i})\sigma_u}}\right)-\Phi\left(\frac{[c_1-\gamma_0-\gamma_0\theta' w_i-\gamma_1 x_{1i}-\gamma_1\theta' w_i x_{1i}]}{\sqrt{(\gamma_0+\gamma_1 x_{1i})^2\sigma_u^2+1+2\kappa_{u,\varepsilon}(\gamma_0+\gamma_1 x_{1i})\sigma_u}}\right)\\
P(H=3) &= \Phi\left(\frac{[c_3-\gamma_0-\gamma_0\theta' w_i-\gamma_1 x_{1i}-\gamma_1\theta' w_i x_{1i}]}{\sqrt{(\gamma_0+\gamma_1 x_{1i})^2\sigma_u^2+1+2\kappa_{u,\varepsilon}(\gamma_0+\gamma_1 x_{1i})\sigma_u}}\right)-\Phi\left(\frac{[c_2-\gamma_0-\gamma_0\theta' w_i-\gamma_1 x_{1i}-\gamma_1\theta' w_i x_{1i}]}{\sqrt{(\gamma_0+\gamma_1 x_{1i})^2\sigma_u^2+1+2\kappa_{u,\varepsilon}(\gamma_0+\gamma_1 x_{1i})\sigma_u}}\right)\\
P(H=4) &= \Phi\left(\frac{[c_4-\gamma_0-\gamma_0\theta' w_i-\gamma_1 x_{1i}-\gamma_1\theta' w_i x_{1i}]}{\sqrt{(\gamma_0+\gamma_1 x_{1i})^2\sigma_u^2+1+2\kappa_{u,\varepsilon}(\gamma_0+\gamma_1 x_{1i})\sigma_u}}\right)-\Phi\left(\frac{[c_3-\gamma_0-\gamma_0\theta' w_i-\gamma_1 x_{1i}-\gamma_1\theta' w_i x_{1i}]}{\sqrt{(\gamma_0+\gamma_1 x_{1i})^2\sigma_u^2+1+2\kappa_{u,\varepsilon}(\gamma_0+\gamma_1 x_{1i})\sigma_u}}\right)\\
P(H=5) &= 1-\Phi\left(\frac{[c_4-\gamma_0-\gamma_0\theta' w_i-\gamma_1 x_{1i}-\gamma_1\theta' w_i x_{1i}]}{\sqrt{(\gamma_0+\gamma_1 x_{1i})^2\sigma_u^2+1+2\kappa_{u,\varepsilon}(\gamma_0+\gamma_1 x_{1i})\sigma_u}}\right)
\end{aligned} \tag{3.8}$$

3.3.3 Identification

In order to clarify the identification of the model, we can write the estimation equation in (3.8) in the following form:

$$\begin{aligned}
P(H=1) &= \Phi\left(\tfrac{c_1}{\psi}-\tfrac{\gamma_0}{\psi}-\tfrac{\gamma_0\theta'}{\psi}w_i-\tfrac{\gamma_1}{\psi}x_{1i}-\tfrac{\gamma_1\theta'}{\psi}w_i x_{1i}\right)\\
P(H=2) &= \Phi\left(\tfrac{c_2}{\psi}-\tfrac{\gamma_0}{\psi}-\tfrac{\gamma_0\theta'}{\psi}w_i-\tfrac{\gamma_1}{\psi}x_{1i}-\tfrac{\gamma_1\theta'}{\psi}w_i x_{1i}\right)-\Phi\left(\tfrac{c_1}{\psi}-\tfrac{\gamma_0}{\psi}-\tfrac{\gamma_0\theta'}{\psi}w_i-\tfrac{\gamma_1}{\psi}x_{1i}-\tfrac{\gamma_1\theta'}{\psi}w_i x_{1i}\right)\\
P(H=3) &= \Phi\left(\tfrac{c_3}{\psi}-\tfrac{\gamma_0}{\psi}-\tfrac{\gamma_0\theta'}{\psi}w_i-\tfrac{\gamma_1}{\psi}x_{1i}-\tfrac{\gamma_1\theta'}{\psi}w_i x_{1i}\right)-\Phi\left(\tfrac{c_2}{\psi}-\tfrac{\gamma_0}{\psi}-\tfrac{\gamma_0\theta'}{\psi}w_i-\tfrac{\gamma_1}{\psi}x_{1i}-\tfrac{\gamma_1\theta'}{\psi}w_i x_{1i}\right)\\
P(H=4) &= \Phi\left(\tfrac{c_4}{\psi}-\tfrac{\gamma_0}{\psi}-\tfrac{\gamma_0\theta'}{\psi}w_i-\tfrac{\gamma_1}{\psi}x_{1i}-\tfrac{\gamma_1\theta'}{\psi}w_i x_{1i}\right)-\Phi\left(\tfrac{c_3}{\psi}-\tfrac{\gamma_0}{\psi}-\tfrac{\gamma_0\theta'}{\psi}w_i-\tfrac{\gamma_1}{\psi}x_{1i}-\tfrac{\gamma_1\theta'}{\psi}w_i x_{1i}\right)\\
P(H=5) &= 1-\Phi\left(\tfrac{c_4}{\psi}-\tfrac{\gamma_0}{\psi}-\tfrac{\gamma_0\theta'}{\psi}w_i-\tfrac{\gamma_1}{\psi}x_{1i}-\tfrac{\gamma_1\theta'}{\psi}w_i x_{1i}\right)
\end{aligned} \tag{3.9}$$

where $\psi^2 = (\gamma_0+\gamma_1 x_{1i})^2\sigma_u^2+1+2\kappa_{u,\varepsilon}(\gamma_0+\gamma_1 x_{1i})\sigma_u$. In this form, we can easily evaluate various aspects of the theoretical model. A basic ordered probit model will allow identification of the following list of coeffcients: $\{\frac{c_1}{\psi}, \frac{c_2}{\psi}, \frac{c_3}{\psi}, \frac{c_4}{\psi}, \frac{\gamma_0}{\psi}, \frac{\gamma_0\theta'}{\psi}, \frac{\gamma_1}{\psi}, \frac{\gamma_1\theta'}{\psi}\}$. These coefficients are contaminated with both cross-sectional variation across individuals (race, gender, income, etc) and life-cycle aspects of health. As we suggested earlier, disantangling those effects without having a mechanism that generates the individul reporting behavior is not an easy task. The thoretical model presented in the previous section does that by accounting for the individuals' lifetime utility from health conditional on observed characteristics. In this section, we show that the model parameters in equation (3.9) are individually identified. Therefore, the utility function in (3.2) is also identified. This will constitute the bottom line of the estimation framework. Since the utility function is specified for a period, the coeffcients $\{\gamma_0, \gamma_1\}$ will indicate the extent of the effect of observed characteristics on the current utility. In general, that kind of information cannot be derived directly from an ordered probit analyisis.

The estimated coefficients may have particularly useful policy implications. We concentrate on a special implication in this paper, which concentrates on the source of the discrepancy in SAH reporting behaviour of men and women. The results presented have direct implications for organizing a policy. If a policy maker only considers raw evidence from the data literally, the data would imply that, on average, women in society are less healthy than men with the same given characteristics. However, this result may not necessarily be true since SAH reports the individuals' own assesment of their current health statuses. Therefore, any heterogeneity in reporting behaviour of individuals possibly can explain the gender differences in reporting. However, as in Soytas and Kose (2013)(110) and Denton et al. (2004)(35), controlling for various observed characteristics and chronic illness does not eliminate gender differences in subjective health status. Additionally, Lindeboom and van Doorslaer (2004)(81) stated that the gender and age of the respondents affect reporting behavior in Canadian survey. The mechanism developed in this paper will address the issue and provide a channel to explain heterogeneity in reporting behavior. Equation (3.9) allows us to identify the individual period utility function coefficients, which are the marginal period benefits from various characteristics in constructing a health utility. We expect smaller effects in the period coefficients, measured by $\{\gamma_0, \gamma_1\}$, than the coeffcients that would be obtained from an ordered probit model, which relies on a generic utility.

The functional form of our model in (3.9) is similar to a specification where a highly nonlinear conditional mean function and heterogenous thresholds are accounted for in an ordered probit estimation. Clearly, the specific form of non-linearity we impose here is a direct result of the theoretical model. The fore-mentioned models are identified under general conditions ((Greene and Hensher (2010a)(51)). The estimation identifies $\{\gamma_0, \gamma_1\}$, which are the coefficients of interest for our purposes. We use the Stata Package for estimating Ordinal Generalized Linear Models (Williams (2010)(124)). This estimation framework addresses the general nonlinear mean function (derived form from the valuation function in terms of parameters and the data in our context) and is capable of allowing to specify for the heteroskedasticity in the unobserved component[4], (which is the term composed of the two normal errors in the model).

3.4 DATA DESCRIPTION

We employ data from the U.S. National Health Interview Survey (NHIS) for 2012. The self-assessed health status is coded as an ordinal variable. The corresponding question for SAH reads: "What is the status of your health?"

$$SAH_i = \left\{ \begin{array}{ll} 1 & \text{if individual reports "Poor"} \\ 2 & \text{if individual reports "Fair"} \\ 3 & \text{if individual reports "Good"} \\ 4 & \text{if individual reports "Very Good"} \\ 5 & \text{if individual reports "Excellent"} \end{array} \right\}$$

We use a dummy variable to control for gender. The female dummy is one if the individual is a female and zero if the individual is a male. Similarly, we construct a dummy variable for marital status. The unmarried category includes single, divorced, widowed, separated and other individuals. We also construct dummy variables for ethnicity groups. We have data on years of education for the respondents. The chronic illness dummy is one if individual

[4] The heteroskedasticity in the unobserved component is a way of using the general framework here. The other approach would account for heterogenous thresholds. One may choose either approach depending on the problem at hand and the structural parameters of interest. However, they do not much differ in terms of construction of the estimation equation.

Table 21: Descriptive Statistics for Year 2012

		All		Male		Female	
		N	% Mean	N	% Mean	N	% Mean
Female		19,080	55.73				
Married*		14,834	43.42	7,175	47.43	7,659	40.24
Age		34,238	48.49	15,158	47.98	19,080	48.90
			(18.15)		(17.59)		(18.56)
Race							
	White	26,034	76.04	11,745	77.48	14,289	74.89
	Black	5,453	15.93	2,147	14.16	3,306	17.33
	Asian	2,230	6.51	1,029	6.79	1,201	6.29
	Other	521	1.52	237	1.56	284	1.49
Education		34,098	14.80	15,083	14.81	19,015	14.79
			(3.42)		(3.45)		(3.40)
Health Status		34,238	3.63	15,158	3.67	19,080	3.60
			(1.09)		(1.08)		(1.09)
	Excellent	8,810	25.73	4,083	26.94	10,340	26.17
	Very good	10,671	31.17	4,770	31.47	12,125	30.69
	Good	9,565	27.94	4,121	27.19	11,253	28.48
	Fair	3,943	11.52	1,678	11.07	4,455	11.28
	Poor	1,249	3.65	506	3.34	1,335	3.38
Chronic Illness		6,227	18.26	2,634	17.43	3,593	18.92
Employment							
	Employed	21,862	63.85	10,588	69.85	11,274	59.09
	Not employed	12,376	36.15	4,570	30.15	7,806	40.91
Ownhouse		20,106	58.80	9,018	59.56	11,088	58.19
Family size		34,238	2.37	15,158	2.31	19,080	2.41
			(1.46)		(1.44)		(1.47)
Family Income**		34,238	54.19	15,158	57.94	19,080	51.21
			(46.56)		(47.62)		(45.48)
# of Children		34,238	0.59	15,158	0.49	19,080	0.66
			(1.04)		(0.97)		(1.09)
BMI		34,238	30.16	15,158	29	19,080	31.07
			(14.28)		(10.05)		(16.84)
Smoking							
	Never	20,225	59.07	7,909	52.18	12,316	59.07
	Former	7,580	22.14	3,964	26.15	3,616	22.14
	Some Day	1,481	4.33	788	5.20	693	3.63
	Every Day	4,952	14.46	2,497	16.47	2,455	12.87

*Single, widowed, divorced and other categories in marital status and coded as "unmarried."
** Family income is represented in thousands of dollars.

has limited activity due to a chronic illness and zero otherwise. We consider a dummy for employment status. Ownhouse dummy is one if the individual is living in a family owned house and zero otherwise. Family size measures the number of people for the household in which the respondent lives. Annual family income corresponds to individual's total family income in thousands of dollars. We have the data for the number of children living in the household in which the respondent also lives. Body mass index is a continuous variable obtained by the ratio of weight and height of the respondent. Smoking data is recoded as a dummy variable according to the degree of smoking habit.

The descriptive statistics for the relevant variables are provided in Table 21. We consider individuals older than the age of 18: a total of 34,238 respondents. Females constitute 55.7% of the sample and 43.42% of the sample are married. The mean age is 48.49 and 76.04% of the sample report their ethnicity as Caucasian. The average year of schooling is 14.8 for the whole sample. 25.73% of all respondents report "excellent" health. Women report lower health statuses on average. Namely, the average health status of men is 3.67 whereas that of women is 3.60. Moreover, 18.26% of the sample report chronic illnesses. 69.85% of males are employed whereas 59.09% of women do have a job which is in line with labor force participation rates in the U.S[5]. The average annual family income for the sample is $54,190. The mean of family size is 2.37 and 58.80% of all respondents live in a family owned house. The average number of children in the household is 0.59 whereas the average body mass index of the sample reads 30.16. Finally, 59.07% of the sample does not as 14.46% smoke everyday.

3.5 ESTIMATION AND RESULTS

We will estimate the dynamic model and extend it by including other controls in the utility for health equation. Enhancing the model will only change the number of parameters to be estimated in reduced form representation in equation (3.9) using the value function form in equation in (3.3). Although this approach will have more parameters to estimate, identifica-

[5] According to World Bank data, female labor force participation rate was 58% whereas male labor force participation rate was 70% in 2010. The total labor force participation rate of the U.S. was 65% in 2010.

tion of the structural parameters in equation (3.9) follows the same line of arguments of the basic model. The proxy variable for the individual discount rate equation will be smoking habits as described in the data set. The unobserved factors are allowed to be dependent and an ordered probiy specification with only linear terms will also be estimated for comparison. The equation in (3.8) fits into the framework of heterogeneous choice/location-scale models (Greene and Hensher (2010a)(51); Williams (2009)(123)). In these models, heterogeneity in response is modeled through various extensions of basic ordered probit/logit models. One of those extensions is modeling the error variance as a function of individual characteristics instead of assuming a constant variance. When an ordinal regression model incorrectly assumes that error variances are the same for all cases, standard errors are not correct and the parameter estimates are biased (Greene and Hensher (2010b)(52); Greene and Hensher (2007)(50)). Heterogeneous choice/location-scale models explicitly specify the determinants of heteroskedasticity in an attempt to correct it. Further, these models can be used when the variance/variability of underlying attitudes is itself of a substantive interest. For instance, Alvarez and Brehm (1995)(2) argued that individuals whose core values are in conflict will have a harder time making a decision about abortion and hence, they will have greater variability/error variances in their responses. Having the heteroscedasticity assumption practically improves estimation fit by modelling the heterogeneity in responses from one aspect; whereas its implications in terms of the estimated model's structural parameters is not clear. However, the model in equation in (3.8), as a solution to a dynamic problem, fits into the estimation framework of heterogeneous choice/ location-scale models. Thus, we conclude that the dynamic model accounting for the heterogeneity in individual responses is likely to improve the fit of the model; which is in line with empirical evidence on heterogeneous choice/ location-scale models (Greene and Hensher (2010a)(51); Williams (2009)(123)). In contrast to empirical applications of the sort mentioned, the structural model gives us an explanation for the differences in response. The contribution of our model is in the identification of the mechanism behind the heterogeneous choice/ location-scale models.

In order to estimate the structural model parameters, we employ Ordinal Generalized Linear Model estimation method proposed by Williams (2010)(124). In Table 22, we report

Table 22: Comparison of Ordered Probit and Structural Model Results

	Ordered Probit	Structual Model	Ratio
Female	-0.04686	-0.03681	1.27309
Age	-0.01089	-0.00965	1.12787
Black	-0.25184	-0.21658	1.16284
Asian	-0.15741	-0.13842	1.13718
Other Race	-0.26283	-0.22504	1.16794
Education	0.05028	0.04349	1.15609
Family Income	0.00298	0.00228	1.30424
Chronic	-1.15312	-1.01383	1.13739

estimation results with ordered probit the first column and second column reports the results for the structural model. Reported, γ, coefficients in the structural estimation are the utility parameters of the race, education, gender, income and chronic illness variables. The changes in the coefficients from the ordered probit model to the structural model results are substantial, which has causal implications on the structural model. The decline in the female coefficient is 21%. Apart from that; all other coefficients drop significantly. These results are consistent with and expected from the framework of forward looking optimization behavior of individuals since utility coefficients now only capture period returns. In the ordered probit estimation, the same factors are loaded with larger effects since they are contaminated with the life-cycle effects. For instance, the coefficient of education in the ordered probit estimation is 0.0502 whereas that coefficient in the structural model is only 0.0434. In terms of explaining the gender gap in self-assessed health status, heterogeneity in the discount factor via our theoretical model explains substantial part of it.

We report detailed estimates of ordered probit model in Table 23 and provide marginal effects in Table 24. Similarly, Table 25 and 26 provide detailed estimation results and marginal effects for the structural model. The estimated relationship between self-reported health status and explanatory variables are in line with previous findings. Namely, self-assessed health statuses are positively associated with income and education whereas it is negatively correlated with age. The non-linear effect of income on self-rated health status is observed in the structural model estimations. Females significantly report lower health statuses than males. African-Americans significantly report lower health statuses than Caucasian respondents. Self-assessed health statuses have negative correlation with chronic illness conditions and smoking habits. There are differences in marginal effects reported by the ordered probit and structural model findings. Although ordered probit estimates reveal significant gender effects on all self-rated health levels, structural model identifies different effects. Ordered probit results imply that females are more likely to report lower levels of health status, i.e. "poor," "fair" and "good" and less likely to report higher levels, i.e. "very good" and "excellent." The structural model identifies gender differences only for reporting "fair," "good" and "excellent" health status. Namely, females are more likely to report "fair" and "good" and less likely to report "excellent" for their health statuses. These results support our hypothesis that there is reporting heterogeneity in self-rated health statuses, mostly explained by heterogeneous individual discount factors of the survey respondent.

Obviously, the estimated relationship via Ordinal Generalized Linear Model estimation method can only reveal the coeffcients associated with the utility parameters (γ) and utility specification. The remaining parameters of the model may be estimated as well to get their numerical values. However, the main interest of this paper focuses on the period utility and a more complex estimation method via maximum likelihood is required for full estimation of the equation in (3.9), which is left for another work. The main finding of the paper is that the heterogenity in SAH response can be accounted to some extent with the inclusion of heterogenity in discount factors. There may be other possible explanations to the abnormality in the data about male-female differences in SAH reporting such as heterogeneity in risk taking and perception of scales for health statuses. The anchoring vignettes is a possible way to check the reporting differences in the individual outcomes. This technique will require some proxy for the actual health outcomes of individuals in the data set. Then, the implied thresholds may be checked with the various health outcomes, such as the tests for diabeties, blood pressure, etc. This method still lacks the mechanism that generates the observed differences, but provides explanations in terms of exploring another form of heterogeneity.

Table 23: Ordered Probit Results

Female	-0.0469***
	[0.0147]
Age	-0.0109***
	[0.000415]
Black	-0.252***
	[0.0196]
Asian	-0.157***
	[0.0272]
Other Race	-0.263***
	[0.0597]
Education	0.0503***
	[0.00221]
Family Income	0.00298***
	[0.000168]
Chronic Illness	-1.153***
	[0.0218]
Smoking	-0.113***
	[0.0313]
Smoking x Female	0.00290
	[0.0110]
Smoking x Age	0.00105***
	[0.00349]
Smoking x Black	0.0463***
	[0.0147]
Smoking x Asian	0.0125
	[0.0267]
Smoking x Other Race	0.0119
	[0.0426]
Smoking x Education	-0.00431**
	[0.00188]
Smoking x Family Income	0.000198
	[0.000152]
Smoking x Chronic Illness	-0.0196
	[0.0144]
Cut 1	-2.286***
	[0.0418]
Cut 2	-1.252***
	[0.0398]
Cut 3	-0.154***
	[0.0394]
Cut 4	0.811***
	[0.0395]
N	33,960

1) White is the base group for the race.
2) Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 24: Marginal Effects for Ordered Probit

Self Reported Health	Poor (1)	Fair (2)	Good (3)	Very Good (4)	Excellent (5)
Probability	0.0109	0.0930	0.3319	0.3534	0.2105
Female	0.00134***	0.00709***	0.0100***	-0.00489***	-0.0136***
Age	0.000314***	0.00165***	0.00232***	-0.00114***	-0.00314***
Black	0.00889***	0.0416***	0.0494***	-0.0324***	-0.0676***
Asian	0.00531***	0.0256***	0.0315***	-0.0196***	-0.0429***
Other Race	0.0102***	0.0452***	0.0492***	-0.0366***	-0.0679***
Education	-0.00145***	-0.00763***	-0.0107***	0.00529***	0.0145***
Family Income	-0.00008***	-0.000452***	-0.000635***	0.000313***	0.000859***
Chronic Illness	0.0824***	0.223***	0.123***	-0.192***	-0.236***
Smoking	0.00324***	0.0171***	0.0240***	-0.0118***	-0.0325***
SmokingxFemale	-0.00008	-0.000441	-0.000619	0.000305	0.000838
SmokingxAge	-0.00003***	-0.000159***	-0.000223***	0.000110***	0.000302***
SmokingxBlack	-0.00133***	-0.00702***	-0.00986***	0.00486***	0.0134***
SmokingxAsian	-0.000361	-0.00190	-0.00268	0.00132	0.00362
SmokingxOther Race	-0.000342	-0.00180	-0.00253	0.00125	0.00342
SmokingxEducation	0.000124**	0.000655**	0.000920**	-0.000454**	-0.00125**
SmokingxFamily Income	-0.000005	-0.00003	-0.00004	0.00002	0.00005
SmokingxChronic Illness	0.000565	0.00298	0.00418	-0.00206	-0.00566

*** p<0.01, ** p<0.05, * p<0.1

Table 25: Structural Model Results

	Self Rated Health	ln(sigma)
Female	-0.0368***	-0.00776
	[0.0126]	[0.0105]
Age	-0.00965***	0.00146
	[0.000656]	[0.00168]
Black	-0.217***	0.0284**
	[0.0210]	[0.0142]
Asian	-0.138***	0.0218
	[0.0241]	[0.0218]
Other Race	-0.225***	0.0550
	[0.0597]	[0.0413]
Education	0.0435***	-0.00746
	[0.00310]	[0.00665]
Family Income	0.00228***	-0.00224***
	[0.000195]	[0.000374]
Chronic Illness	-1.014***	0.175***
	[0.0629]	0.0149
Smoking	-0.109***	
	[0.0313]	
Smoking x Female	0.00180	
	[0.00950]	
Smoking x Age	0.000975***	
	[0.000308]	
Smoking x Black	0.0336**	
	[0.0133]	
Smoking x Asian	0.0101	
	[0.0227]	
Smoking x Other Race	0.0112	
	[0.0393]	
Smoking x Education	-0.00294*	
	[0.00173]	
Smoking x Family Income	0.000199	
	[0.000125]	
Smoking x Chronic Illness	-0.0285**	
	[0.0142]	
Age^2	-0.000015	
	[0.0000161]	
$Education^2$	-0.000146	
	[0.000263]	
$Family Income^2$	0.0000083***	
	[0.000002]	
Cut 1	-2.103***	
	[0.133]	
Cut 2	-1.089***	
	[0.0755]	
Cut 3	-0.123***	
	[0.0365]	
Cut 4	0.677***	
	[0.0516]	
N	33,960	

1) White is the base group for the race.
2) Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 26: Marginal Effects for Structural Model

Self Reported Health	Poor (1)	Fair (2)	Good (3)	Very Good (4)	Excellent (5)
Probability	0.0073	0.0981	0.3469	0.3407	0.2066
Female	0.000492	0.00559**	0.0106***	-0.00255	-0.0141***
Age	0.000304***	0.00210***	0.00215***	-0.00166***	-0.00289***
Black	0.00852***	0.0497***	0.0421***	-0.0399***	-0.0604***
Asian	0.00543***	0.0321***	0.0269***	-0.0260***	-0.0383***
Other Race	0.0123***	0.0571***	0.0327**	-0.0480***	-0.0540***
Education	-0.00141***	-0.00959***	-0.00953***	0.00773***	0.0128***
Family Income	-0.000166***	-0.000833***	-0.000166**	0.000924***	0.000241**
Chronic Illness	0.0987***	0.241***	0.0660***	-0.199***	-0.207***
Smoking	0.00260***	0.0206***	0.0272***	-0.0141***	-0.0363***
SmokingxFemale	-0.00004	-0.000341	-0.000450	0.000233	0.000601
SmokingxAge	-0.00002***	-0.000185***	-0.000244***	0.000126***	0.000326***
Smoking Black	-0.000803**	-0.00638**	-0.00841**	0.00436**	0.0112**
SmokingxAsian	-0.000241	-0.00192	-0.00252	0.00131	0.00337
SmokingxOther Race	-0.000268	-0.00213	-0.00281	0.00146	0.00376
SmokingxEducation	0.00007*	0.000559*	0.000736*	-0.000381*	-0.000984*
SmokingxFamily Income	-0.000004	-0.00003	-0.00004	0.00002	0.00006
SmokingxChronic Illness	0.000681**	0.00541**	0.00713**	-0.00369**	-0.00953**
Age^2	-0.0000007	-0.000002	0.000002	0.000004	-0.000003
Education^2	-0.000007	-0.00002	0.00002	0.00004	-0.00003
Family Income^2	0.0000004***	0.000001***	-0.000001***	-0.000002***	0.000001***

*** p<0.01, ** p<0.05, * p<0.1

3.6 CONCLUSION

There are significant gender differences in self-assessed health statuses. Male survey respondents significantly report higher subjective health statuses then their female counterparts. Biological factors, socioeconomic factors or a combination of both are stated as explanations for the gender gap. The gender effect significantly persists even if different factors and social mechanisms are taken into account (Walters et al. 2002(121); Denton et al. 2004(35); Soytas and Kose (2013)(110)). Reviewing previous findings, Soytas and Kose (2013)(110) showed that there remains a significant gender gap in self reported health status even after control of chronic illness conditions unlike the earlier findings (see Case and Paxson 2005 (21); Malmusi et al. 2012(83)). There is also evidence of reporting heterogeneity in self-assessed health statuses indicated in Canadian, American and Turkish data (Lindeboom and van Doorslaer 2004(81); Soytas and Kose (2013)(110)).

Given the attempts and explanations provided by the literature, there still remains an unexplained significant portion of the gender gap in self-reported health statuses. In an effort to fill this gap and provide a more robust framework to explain the gender gap in self-reported health levels, we present a theoretical identification mechanism via a dynamic set-up. The model asserts that the current utility associated with the current health state is the solution to a dynamic problem, which includes discounted sums of future utilities. The theoretical model takes heterogeneity in individual discount rates into account and provide an identification mechanism. We hypothesize that heterogeneity in individual discount rates would lead to reporting heterogeneity in self-assessed health status. Thus, this paper suggests that the gender differences in subjective discount rates could crucially affect self-reported health levels of individuals.

Employing the U.S. National Health Interview Survey of 2012 and using smoking habits as a proxy for individual discount rates, we estimate the structural model coefficients and compare them with an ordered probit estimation. Supporting the theoretical predictions, results indicate magnitude differences across the coefficients of ordered probit model and the structural model. Moreover, structural models identify different marginal effects of being female on likelihood of reporting various subjective health status levels. The main finding of the paper is that the heterogenity in SAH response can be accounted to some extent with the inclusion of heterogenity in discount factors. This paper presents theoretical and empirical results to show that a puzzle in health outcomes, i.e., the gender gap in self-assessed health status, may be substantially explained once the differences in stochastic discounting are taken into account. Thus, policy makers and future research should take heterogeneity in individual discount rates into account when addressing the gender differences in health outcomes. However, the findings of the paper should be treated as an upper bound for the effect of heterogeneity individual discount rates on subjective assessment of health levels. Heterogeneity in risk taking, perception of scales, framing effects and unobserved factors in smoking habit may also contribute to reporting heterogeneity in self-rated health status. Future work should consider direct measures of indvidual discount factors and risk taking behavior of individuals to identify their effects on the gender gap in self-reported health statuses.

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APPENDIX

APPENDIX FOR CHAPTER 1

A. DERIVATION OF FUNDAMENTAL VALUES

Fundamental Value for Treatment 3

In two markets of this treatment, there is a change in the bankruptcy probability and thus fundamental value calculations are adjusted accordingly for these markets. The realized fundamental value of an asset for period 1, of the second market in session 1, is given by the following:

$$FV(1) = \sum_{s=1}^{16}(0.875)^{s-1}\frac{1}{2}(57-s) + \sum_{s=17}^{20}(0.875)^{s-1}\frac{1}{2}(57-s) + \sum_{s=21}^{\infty}(0.875)^{s-1}\frac{1}{2}(57-s)$$

I calculate the corresponding values for first two sums and approximate the last term by the following summation since the discounting term will be close to zero for further terms. Fundamental values for other periods and second session are calculated in a similar fashion.

$$\sum_{s=21}^{\infty}(0.875)^{s-1}\frac{1}{2}(57-s) \approx \sum_{s=21}^{100}(0.875)^{s-1}\frac{1}{2}(57-s)$$

Fundamental Value for Treatment 4

In two markets of this treatment, there is a change in the bankruptcy probability and thus fundamental value calculations are adjusted accordingly for these markets.The realized fundamental value of an asset for period 1, of the fourth market in session 1, is given by the following:

$$FV(1) = \sum_{s=1}^{12}(0.875)^{s-1}\frac{s}{2} + \sum_{s=13}^{\infty}(0.75)^{s-1}\frac{s}{2}$$

I calculate the corresponding values for first two sums and approximate the last term by the following summation since the discounting term will be close to zero for further terms. Fundamental values for other periods and the third market of the second session are calculated in a similar fashion.

$$\sum_{s=13}^{\infty}(0.75)^{s-1}\frac{s}{2} \approx \sum_{s=13}^{100}(0.75)^{s-1}\frac{s}{2}$$

B. EXPERIMENT INSTRUCTIONS

I provide experimental instructions for Treatment 3, i.e. decreasing fundamentals, in this section. Instructions for other treatments of the experiment are similar and available upon request.

1. General Instructions

Welcome to today's experiment. This is an experiment on economic decision making. Please read the instructions carefully since they explain how you will earn money from decisions you make throughout the experiment. Your earnings from the experiment will be paid to you in cash at the end of the session. Please do not talk to any other participants during the experiment. If you have any questions, raise your hand and an experimenter will come to you to answer it.

2. Description of the Market

In this experiment you will have an opportunity to buy and sell in a market by using experimental cash. The experimental cash (EC) will be converted into dollars at the end of the session. The exchange rate will be 2000 EC = $1. At the start of the experiment, you will have a portfolio which consists of Assets (A) and experimental cash (EC). Your starting portfolio will be randomly assigned by the computer and will be one of the following: Portfolio 1 = (20A, 3000 EC) or Portfolio 2 = (60A, 1000 EC). There are 10 participants in today's experiment. Half of the participants will have Portfolio 1 whereas the other half will start with Portfolio 2. Thus, you have an equal chance of receiving Portfolio 1 or 2.

Once the experiment starts, you will see the number of assets and the amount of experimental cash you have on the screen. The experiment consists of a number of trading periods. Each trading period lasts 2 minutes. The number of trading periods will be randomly determined; this process is explained below. Within each trading period, you can buy and sell assets. You will see the time left in the trading period on your computer screen. Your assets and experimental cash balance will carry over to the next period if the experiment continues for another period.

3. Properties of the Asset

At the end of each period, you will receive a return (dividend) for each unit of the asset you hold. There will be two potential dividend amounts, 0 or 57-t, in each period, where t is the number of the period you are in. The computer randomly determines whether you receive 0 EC or 57-t EC for each unit of the asset. Each outcome is equally likely. Note that if the market reaches the 57th period, the asset will pay a dividend of 0 EC. Moreover, if the market continues for more than 57 rounds, the dividend payments (57-t) will be negative. Namely, you may lose some experimental cash depending on the dividend payment of the asset after period 57.

Probability	Dividend
50%	0
50%	57-t

The table indicates that the expected dividend of an asset will be (0.50 * (0) + 0.50 * (57-t)) = 28.5-0.5*t for period t. Note that the amount of EC paid in one period will not affect the amount of EC paid in any other period. At the end of each period, the dividend amount will be determined and your holdings will be updated accordingly. The potential dividend payments for each period are listed in the Information Table below. For example, if the period 5 is reached, 0 EC and 52 EC are possible dividends. If the period 22 is reached, 0 EC and 35 EC are possible dividend payments.

4. Use of Computerized Trading System

Within each trading period, you can buy and sell assets. In order to buy units of Asset (A), you need to have experimental cash and pay the transaction price. You may sell your assets and receive an amount of experimental cash equal to the transaction price. You can increase your cash holdings by selling an asset. Buying an asset will decrease your cash holdings. You can buy and sell units of Asset by posting "bids" (offers to buy) and "asks" (offers to sell) which are described below.

If you would like to sell an asset you can submit an "ask" by inputting the price and quantity of the assets you are willing to sell at that price. If one of the other participants accepts your ask, then you sell the number of assets s/he buys and your experimental cash holdings will increase by the transaction price.

If you would like to buy an asset you can submit a "bid" by inputting the price and quantity of the assets you are willing to buy. If one of the sellers accepts your bid, then you get the asset and pay for it. Then your experimental cash holdings will decrease by transaction price.

Just as you can post "bids" and "asks", you can also buy or sell assets from the "bids" and "asks" posted by other participants.

You can buy and sell more than one unit of the asset in a given period. When the trading period ends, your asset holdings and cash balance will be updated. During each period, as long as you have sufficient assets and cash balance, you may buy and sell assets as often as you like.

You can submit your asks (i.e. your offers to sell) and bids (your offers to buy) at prices ranging from 0 to 999 EC. For every bid/ask you make, you have to enter the number of assets you would like to trade as well. You can submit more than one bid/ask but you cannot cancel your bids/asks. Note that your asset holdings cannot be less than zero.

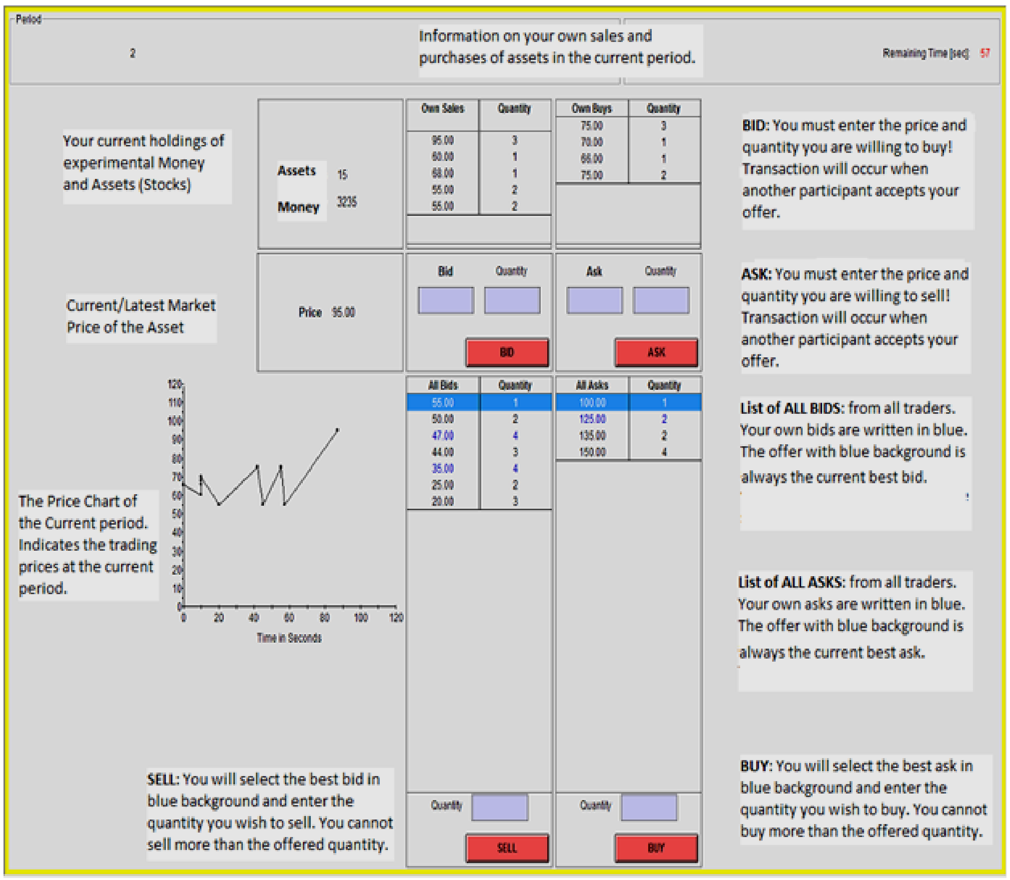
The figure below shows the trading screen you will use during the experiment. It explains how you trade in the market. Please analyze it carefully and if you have any questions, please raise your hand. Note that the numbers in the figure are just examples.

5. Time Horizon and Average Holding Value Table

In this market, the number of trading periods will be randomly determined. After a trading period ends, whether you proceed to the next period will be determined randomly. This randomization occurs by rolling an 8 sided die. This die has 8 sides numbered from 1 to 8. After each trading period, one of the participants will roll the die. If the die lands on a number larger than 1, the market proceeds to another trading period. If the die lands on 1, the market will end. Notice that at the end of a trading period the probability of having one more trading period is 87.5% whereas the probability of the market ending is 12.5%.

After a market ends, you MAY be asked to participate for another market in identical conditions. Note that each market may have a different number of trading periods, depending on chance (i.e. die roll). Moreover, if any of the markets you participate in does not end in the given amount of time for experiment,

Figure 5: Double Auction Trading Screen



the experimenter keeps rights to change the market ending probability to finish the experiment and randomly determine the number of trading periods.

You can use the information on the Average Holding Value table to help you make decisions. The first column indicates the current period during which the average holding value is calculated. The expected dividend column reveals the expected experimental cash payments of an asset in each period. The third column indicates the average holding value of an asset at a given period. The average holding value indicates the expected future earnings from each stock that you hold for the rest of the market. Given the properties and market continuation probability, the average holding value (AHV) an asset in this market is calculated by the following formula.

AVH =200 - 4t for any period t=1, 2, 3 . . . .

For example, at period 11, AVH becomes 200-4*11=156. At period 21, AVH becomes 200-4*21=116. Note that the AVH table displays the potential rounds to which the market game may reach. The full table for potential rounds is given at the end of instructions.

6. Payment

At the end of each trading period, your holdings will possibly consist of assets and/or experimental cash. The market will end if the die reads 1 and your assets will be worthless at the end of the experiment. Thus, you will have only experimental cash. Using the conversion rate 2000 experimental currency = $1, the computer will calculate your dollar earnings. Since the end of the experiment will be randomly determined, the computer will calculate your potential earnings for each period. When a trading period ends, you will be able to see dollar value of your experimental cash holdings. This value is calculated by the following formula: Dollar Value of Your Portfolio= (Money)/2000. This will be your earnings from the experiment if the die reads one at the end of that period. Your total payment will be your earnings from the experiment plus a show up fee of $5. If you participate in more than one market, one of the markets will be randomly selected to determine your payment for the experiment. The experimenter may label the market numbers and put them in an urn and may ask you to pick a number from the urn. Or you may be asked to roll a die to determine the market for payment. Then, you will be paid for selected market and you will also receive the show up fee.

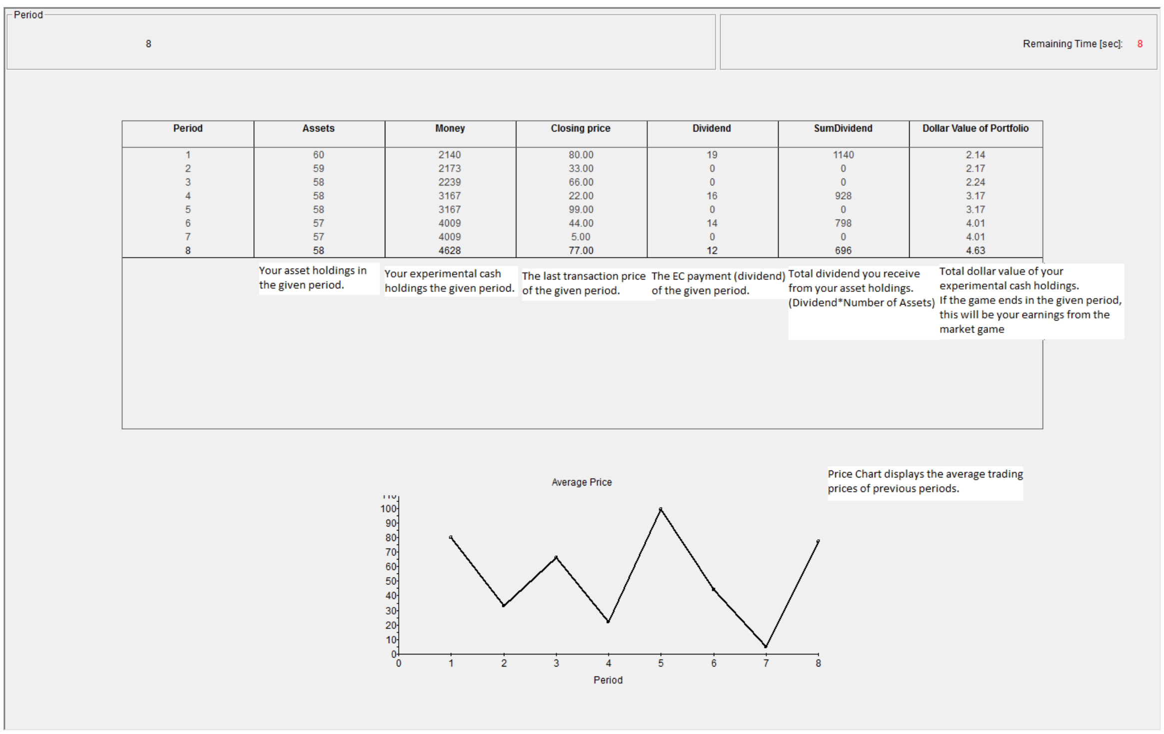
7. History Screen

The following figure is an example of the history screen you will see at the end of each period. When you see this information, the experimenter will stop the experiment and the die roll will determine whether the experiment will continue or not. Please analyze it carefully and if you any questions, raise your hand. Note that the numbers in the figure are just examples and you may face with different numbers during the experiment.

8. Die Roll Screen

After each trading period, you will face with the following DIE ROLL screen. Please wait for the die roll and use the earnings table to write down "Dollar Value of Your Portfolio" if the market ends. Please

Figure 6: Trading Period History Screen



Period	Assets	Money	Closing price	Dividend	SumDividend	Dollar Value of Portfolio
1	60	2140	80.00	19	1140	2.14
2	59	2173	33.00	0	0	2.17
3	58	2239	66.00	0	0	2.24
4	58	3167	22.00	16	928	3.17
5	58	3167	99.00	0	0	3.17
6	57	4009	44.00	14	798	4.01
7	57	4009	5.00	0	0	4.01
8	58	4628	77.00	12	696	4.63

DO NOT click on "CONTINUE" button before the experimenter tells you to do so.

9. Review Questions/Quiz

Q1: How many trading periods you will have in this market?

a) 5 b) 15 c) Depends on the roll of the die.

Q2: How much time will you have for trading in each period?

a) 120 seconds b) 90 seconds c) 60 seconds

Q3: Will the assets you hold always pay experimental cash of 0?

a) Yes b) No c) Depends on the computer's choice.

Q4: Is it possible that your asset holdings will have negative returns?

a) Yes b) No c) Depends on computer's choice and die roll.

Q5: Will you learn the dividend payment of the asset at the beginning of trading period?

a) Yes b) No c) Depends on computer's choice.

Q6: If the market reaches period 16, what will be the average holding value of an asset in this period?

a) 96 b) 136 c) 146 d) 166

Q7: If you hold 50 Assets and 2000 Experimental Cash at the end of a trading period and the die reads 2, what will be your earnings from the experiment including show up fee?

a) 2 b) 7 c) Do Not Know

Summary of Important Information

1. Each trading period lasts for 120 seconds.
2. The assets have dividend of 0 EC or 57-t EC with equal probability at the end of each period t.
3. The market ends (when the die reads 1) at the end of a period with a probability of 12.5%.
4. Each unit of the asset will be worthless when the market ends.

C. ANALYSIS FOR TREATMENT 0

In this section, I analyze the data for Treatment 0, i.e. constant fundamental value treatment of Kirchler et al. (2012)(74). Figures 9 and 10 present trend of transaction prices for six market sessions lasting 10 periods. As noted above these markets are identical with Treatment 1, except the fixed number of trading periods.

Overall, prices and fundamentals exhibit similar trends except session four which reveals 30% underpricing on average according to Table 27. Although comparison tests, presented in Table 28, reveal significant

price deviation for most markets, bubble measures imply that deviations are less than 4% on average for most markets. Thus, Treatment 0 and Treatment 1 of our study reveal similar outcomes in terms of transaction prices. The convergence to fundamental value occurs from below in session three and from above in session five. In other sessions, transaction prices are both below and above the fundamental value for different periods. The evidence on portfolio adjustments is mixed. According to Table 27, stock holdings of subjects are more balanced in session three. Fourth session has the highest concentration ratio, 0.77, for end

Figure 7: Die Roll Screen

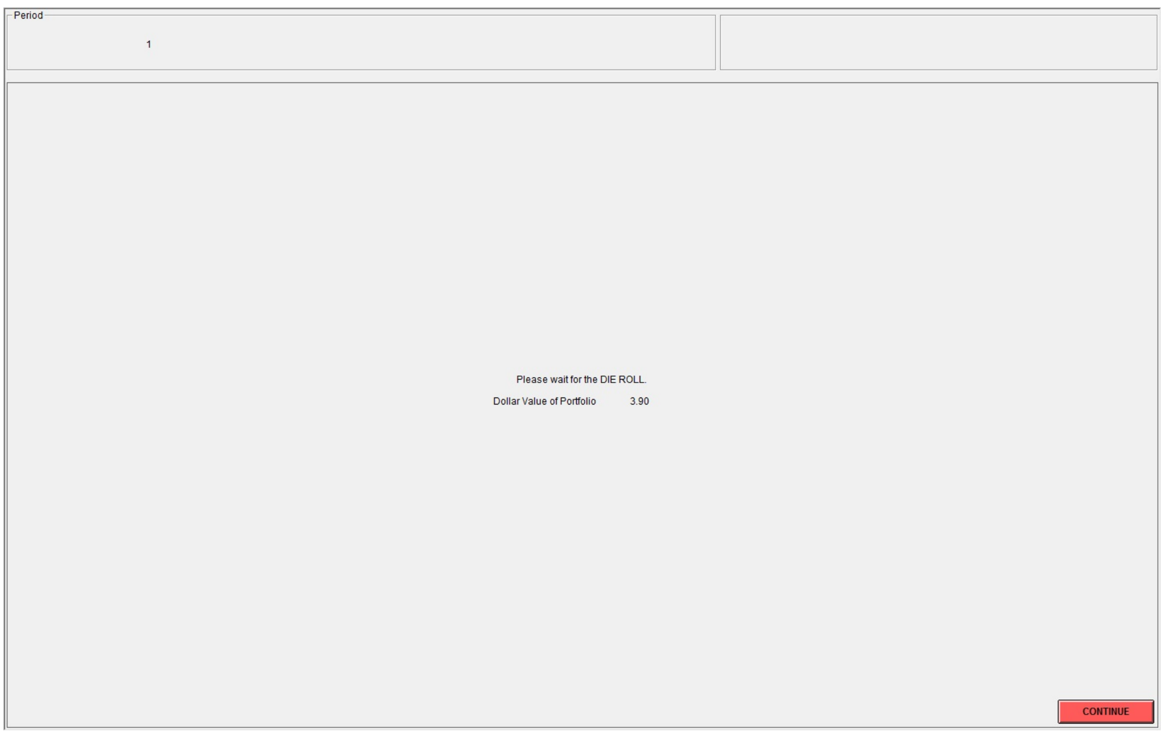


Figure 8: Average Holding Value: Information Table

Average Holding Value: Information Table			
Period	Potential Dividends	Expected Dividend	Average Holding Value
1	0 or 56	28	196
2	0 or 55	27.5	192
3	0 or 54	27	188
4	0 or 53	26.5	184
5	0 or 52	26	180
6	0 or 51	25.5	176
7	0 or 50	25	172
8	0 or 49	24.5	168
9	0 or 48	24	164
10	0 or 47	23.5	160
11	0 or 46	23	156
12	0 or 45	22.5	152
13	0 or 44	22	148
14	0 or 43	21.5	144
15	0 or 42	21	140
16	0 or 41	20.5	136
17	0 or 40	20	132
18	0 or 39	19.5	128
19	0 or 38	19	124
20	0 or 37	18.5	120
21	0 or 36	18	116
22	0 or 35	17.5	112
23	0 or 34	17	108
24	0 or 33	16.5	104
25	0 or 32	16	100
...	...	...	...
30	0 or 27	13.5	80
...	...	...	...
35	0 or 22	11	60
...	...	...	...
40	0 or 17	8.5	40
...	...	...	...
45	0 or 12	6	20
...	...	...	...

Figure 9: Trading Prices for Treatment 0 (Constant Fundamentals with Terminal Value)

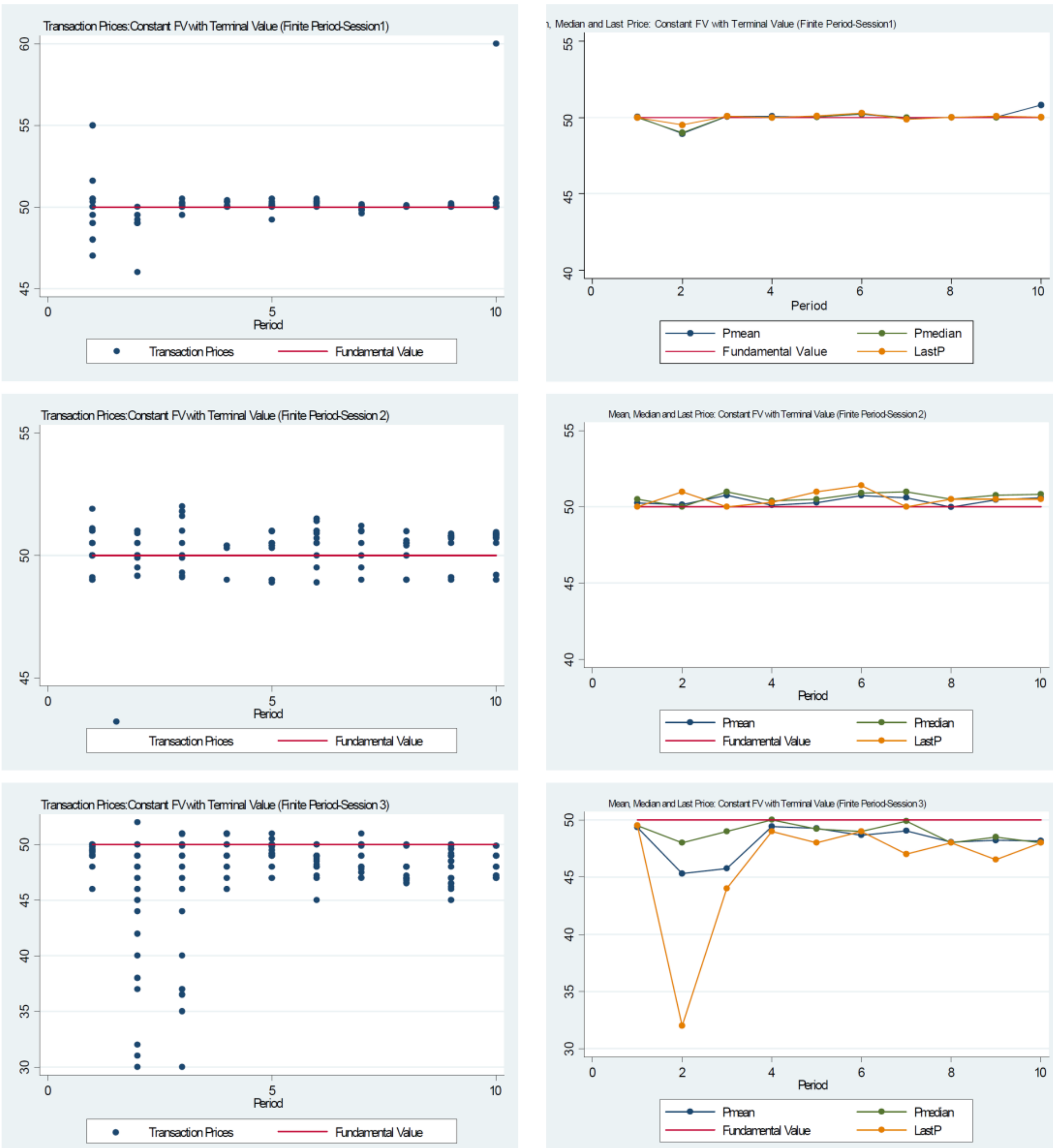


Figure 10: Trading Prices for Treatment 0 (Constant Fundamentals with Terminal Value)

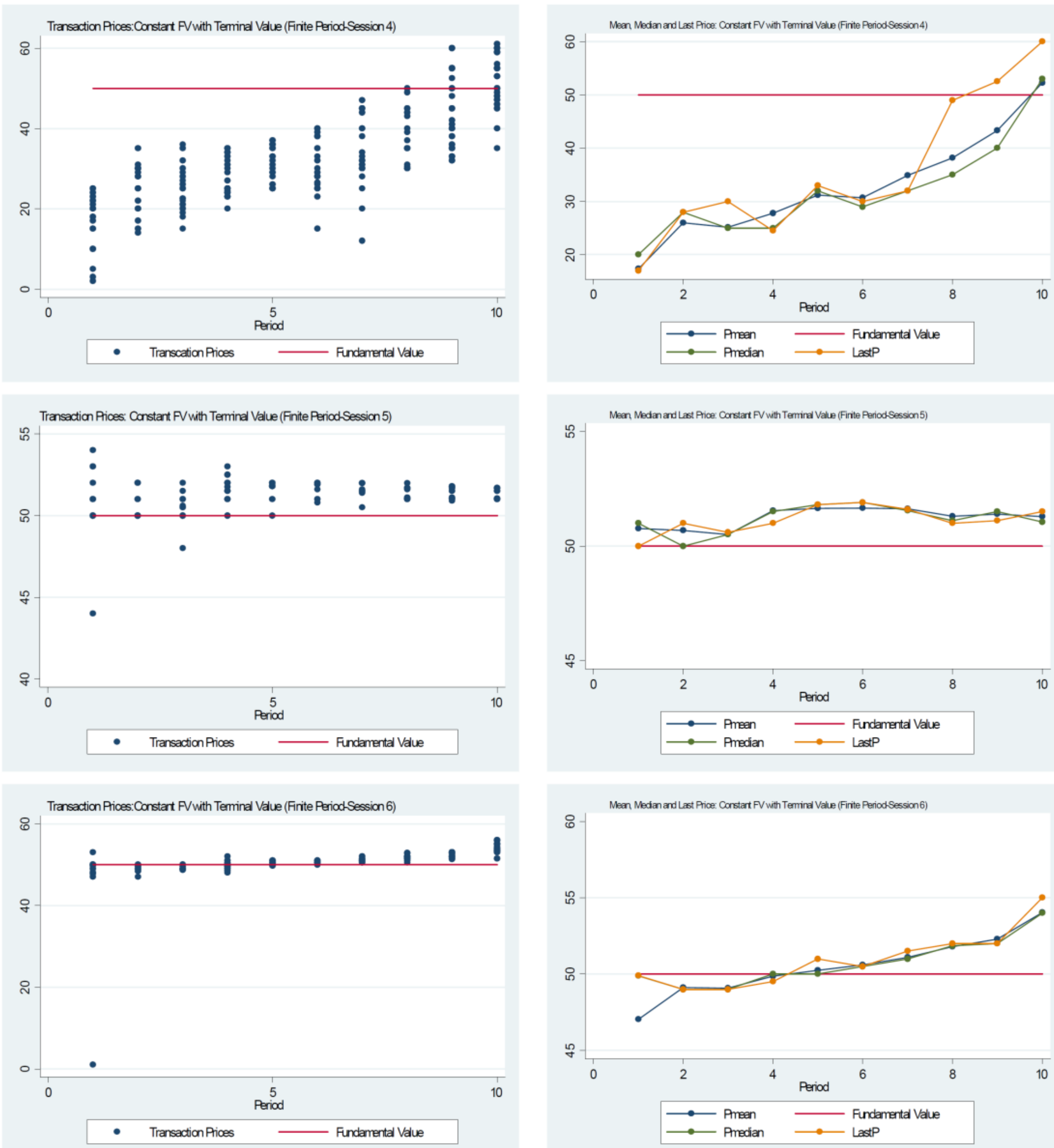


Table 27: Bubble Measures and Gini's Concentration Ratios: Treatment 0

	Session 1	Session 2	Session 3	Session 4	Session 5	Session 6
Bubble Measures						
RAD	0.0042	0.006	0.040	0.362	0.024	0.034
RD	-0.0007	0.006	-0.040	-0.355	0.024	0.005
N	10	10	10	10	10	10
End of Market Gini Concentration Ratio's						
Endowment	0.25	0.25	0.25	0.25	0.25	0.25
Market	0.54	0.51	0.37	0.77	0.48	0.66

of market distribution of asset holdings. Ranging from 0.37 to 0.77, the concentration ratios of treatment zero are higher than that of treatment one. Finally, Table 28 provides mixed test results for the comparison of prices in Treatments 0 and 1. Namely I test the hypothesis that transaction prices in markets of treatment zero is equal to transaction prices in markets of treatment one. Weighted mean prices significantly differ across some markets of two market treatments. For instance, z-values for mean price comparison for market four and five of Treatment 0 and markets of Treatment 1 are significant at 5% level. However, comparison of prices for market six provides insignificant z-statistics: -0.70 and 0.14 for market two and three of treatment one, respectively.

Table 28: Wilcoxon signed-rank tests for Weighted Mean Prices: z values

H$_o$: Prices (M$_i$) = Prices(M$_j$) $i \in \{1, 2, 3, 4, 5, 6\}$ and $j \in \{1, 2, 3\}$			
	Treatment 1		
Treatment 0	Market 1	Market 2	Market 3
Market 1	-2.80***	-1.82*	-0.28
Market 2	-2.80***	-2.52**	-1.26
Market 3	-1.27	1.68*	1.82*
Market 4	-2.59***	-2.52**	2.52**
Market 5	-2.80***	-2.52**	-2.38**
Market 6	-2.59***	-0.70	0.14

1) I consider first markets of each session for Treatment 1 and all markets of Treatment 0.

2) Quantity weighted mean prices are compared across markets.

3) * p<0.1, ** p<0.05, ***p<0.01.

Table 29: Paired t and Wilcoxon signed-ranked tests for Treatment 0: All Transaction Prices,Weighted Mean Prices, Fundamental Values: t and z values

	H$_o$: Prices=Fundamentals					
	Session 1	Session 2	Session 3	Session 4	Session 5	Session 6
t(all)	0.34	7.15***	-10.96***	-16.01***	16.24***	3.79***
z(all)	2.72***	5.48***	-13.99***	-15.23***	10.18***	7.81***
N	174	171	343	358	157	272
t(mean)	-0.26	5.14***	-3.54***	-5.71***	7.91***	0.31
z(mean)	1.37	2.80***	-2.80***	-2.70***	2.80***	0.76
N	10	10	10	10	10	10

1) * p<0.1, ** p<0.05, ***p<0.01.