Ari Hyytinen – Hanna Putkuri

# Household optimism and borrowing

SUOMEN PANKKI · FINLANDS BANK
EUROJÄRJESTELMÄ
EUROSYSTEMET

Bank of Finland Research
Discussion Papers
21 • 2012

# Household optimism and borrowing*

Ari Hyytinen
University of Jyväskylä and Yrjö Jahnsson Foundation

Hanna Putkuri
Bank of Finland

May 7, 2012

**Abstract**

A unique Finnish household-level data from 1994 to 2009 allow us to measure how households' financial expectations are related to the subsequent outcomes. We use the difference between the two to measure forecast errors and household optimism and link the errors to households' borrowing behaviour. We find that households making greatest optimistic forecast errors carry greater levels of debt and are most likely to suffer from excessive debt loads (overindebtedness). They also are less attentive to forecast errors than their pessimistic counterparts when forming their expectations for a subsequent period.

**JEL**: D21, L20
**Key words**: forecast errors, ex ante optimism, borrowing

*We would like to thank seminar participants at HECER (2012), Bank of Finland (2012) and ESEM-EEA (Oslo 2011), as well as Iftekhar Hasan, Markku Kaustia, William Kerr, Karlo Kauko, Steven Ongena, Jouko Vilmunen, and George Waters for helpful discussions. This work was initiated when Hyytinen was visiting Bank of Finland, whose hospitality is greatefully acknowledged. Corresponding author: Ari Hyytinen, School of Business and Economics, University of Jyväskylä, P.O. Box 35, 40014 University of Jyväskylä, Finland. Email: ari.t.hyytinen@jyu.fi.

# 1 Introduction

It is often argued that people are - at least in certain decision-making contexts - prone to make forecast errors that are consistent with them holding (overly) optimistic expectations.[1] There are, however, only relatively few studies that measure forecast errors using deviations of subjective expectations from actual realizations and that, in particular, study the behavioral consequences and sources of such forecast errors and optimism. Two important exceptions are Souleles (2004) and Puri and Robinson (2007).[2] Souleles uses the Michigan Survey of Consumer Attitudes and Behaviour together with the Consumer Expenditure Survey to document that optimistic forecast errors are negatively related to consumption. Puri and Robinson report, in turn, that there is considerable heterogeneity in the degree of optimism across U.S. households as measured by a life-expectancy indicator and that extreme (as opposed to moderate) optimism covaries positively with non-prudent economic behaviour.

This paper builds on these analyses and explores specifically the notion that (larger) optimistic forecast errors are associated with sub-optimal decision-making: Does the notion generalize to other, non-U.S. institutional environments and decision-making contexts? In particular, does it apply to household borrowing behaviour?[3] These questions await for an answer, as it has been

[1] See, e.g., Puri and Robinson (2007) and the literature cited therein. There are three types of overconfidence (Moore and Healy 2008): Overestimation, which refers to a miscalibrated forecast relative to the objective likelihood of an event; overplacement, which results in the better-than-average -effect (i.e., interpersonal optimism); and overprecision, which is about the tendency of people to be overly confident about the accuracy of their forecasts. This paper focuses on the first of these, but instead of term "overestimation" (or "underestimation"), we use term "optimism" (or "pessimism").

[2] See also Hayashi (1985), Pistaferri (2001) and Kaufman and Pistaferri (2009), who evaluate the sensitivity of consumption to income shocks using elicited expectations data, as well as Manski (2004) and Jappelli and Pistaferri (2010), who review the empirical literature on the use of subjective expectations data from various angles. There also is an established strand in the literature that evaluates the rationality of survey expectations (but that do not typically link them to behavior; see Souleles 2004, Section 1, for a review) and that studies how income expectations are related to subsequent realizations (see Dominitz 1998 and Das and Van Soest 1999).

[3] Puri and Robinson document that their measure of optimism correlates positively with the balance payment habits of the U.S. credit card holders. This is an important prior result

argued that both behavioral biases and low debt literacy might be related to household overindebtedness and to the recent problems in the markets for consumer credit and mortgages (Inderst 2008, Lusardi and Tufano 2009, Stango and Zinman 2009; see also Campbell, Jackson, Madrian and Tufano 2011).

To propose that households accumulate too much debt is at odds with the standard economic view on consumption and borrowing behaviour. The large and growing literature on consumption typically postulates that households use unsecured (Sullivan 2008) and secured (Hurst and Stafford 2004) debt to smooth and boost their consumption (see also Alessie and Lusardi 1997 and Mian and Sufi 2011) or that they are unable to borrow as much as they need (see, e.g., Zeldes 1989 and the reviews by Jappelli and Pistaferri 2010 and Attanasio and Weber 2010).[4] The recent analyses of overindebtedness and behavioral biases in the market for debt question the view that these are the only mechanisms at work, but the evidence that backs the alternative views is still limited.

Our data come from Finland, takes the form of a rotating panel and cover a large number of households over a 15-year period from 1994 to 2009. These data are particularly convenient for our purposes: First, the data are nationally representative and allow us to measure how households' financial expectations are related to the subsequent outcomes at the level of individuals (households). We can thus use the difference between the two as a direct indicator of the size and nature of households' forecast errors. The survey questions on which our analysis relies are nearly identical to those studied by Souleles (2004), underlying the Index of Consumer Sentiment in the U.S. Second, unlike the other data sets available to date, the Finnish data allow us to link the forecast errors to

on which we build and that we try to generalize. We ask, in particular, if and how this finding can be generalized to other institutional environments and dimensions of household borrowing behavior, such as having too much debt (overindebtedness).

[4] Other means to smooth consumption are running down savings and resorting to various self-insurance mechanisms, such as intra-family transfers and postponing the purchase of durable goods, and/or reliance on government support programs and unemployment benefits; see Sullivan (2008) and Jappelli and Pistaferri (2010) for references that study these.

households' borrowing behaviour and measures of overindebtedness. Third, the short panel dimension of the data allow an analysis of how households update their expectations in the face of forecast errors.

Our main findings can be summarized as follows:

First, consistent with the earlier U.S. evidence (Souleles 2004; Puri and Robinson 2007), we find that household expectations are, in general, inefficient and vary systematically with the observables. We find, moreover, that after conditioning flexibly on age, cohort and time effects (as well as on a number of demographic variables), having more education is inversely related with making optimistic forecast errors. Unlike the prior studies, we document that the effect is robust to controlling for the (past) level of and contemporaneous shocks to disposable income, as well as for variation in regional housing prices. This finding suggests, but does not prove conclusively, that more education makes people less prone to make optimistic forecasts ex ante.

Second, we find that households that make the greatest optimistic forecast errors are most indebted and most likely to report that they are overindebted (and have other problems with their debts and bills). These results, too, are robust to controlling flexibly for age, cohort and time effects and for the contemporaneous shocks in disposable income. The results support neither the standard view on households' limited access to debt nor use of debt as a safety net (for consumption smoothing). However, our findings square nicely with the results of Puri and Robinson (2007), who show that extreme optimism covaries positively with non-prudent economic behaviour. They also complement the prior studies which suggest that behavioral biases in the market for debt may be empirically important.

This paper also takes a look at the sources of optimistic expectational errors. We do so by examining whether there is something special in how those making optimistic forecast errors update their (financial) expectations. In spirit of the recent literature on consumer inattentiveness (see, e.g., Reiss 2006), we focus on the possibility that those who make the largest optimistic forecast errors are less attentive to the errors than others when they form their expectations. Clearly, this is a first step only, as a complete characterization of the sources of household optimism calls for more detailed data than appears to be currently available. We can, however, show that households are *not* inattentive to past forecast errors. In particular, we find that the probability that a household expects a better (worse) development over a subsequent period is lower for the households for whom the forecast error indicates optimism (pessimism). This relation is consistent with households adjusting their expectations and reacting to past forecast errors. However, this adjustment is found to be asymmetric: Households that make most optimistic errors update their expectations less than those who make pessimistic forecast errors of similar magnitude.

Taken together, our findings portray an elementary process via which optimism may be at work in the market for household debt: Households that make most optimistic forecast errors apparently believe that their errors call for smaller expectational adjustments than the errors of those households that make pessimistic errors of similar magnitude. This asymmetry is consistent with the former being at risk of pursuing non-prudent borrowing behaviour and accumulating gradually greater but potentially unsustainable levels of debt. This, in turn, is line with the most optimistic households reporting that they are overindebted. This behavioral process may sound overly simplistic to many, but seems to have been overlooked in the empirical literature on household debt market behaviour so far.

This paper is organized as follows. In Section 2, we provide a brief review of the related literature. Section 3 describes the data. Section 4 analyses the link between households' forecast errors and borrowing behaviour. Section 5 then studies how attentive households are to the forecast errors. Section 6 offers concluding remarks.

## 2 Related analyses

This paper stands at the cross-road of two related, but distinct strands of economic and finance literatures.[5] Taking each of them in turn:

First, there is a small but growing strand in the empirical economic and finance literature on the behavioral consequences of households' expectational biases and errors. A particular challenge that the analyses in this strand face is that there are only few data sets that allow one to measure both expectations and their subsequent realizations simultaneously with economic outcomes/choices at the level of individuals (or households).[6] The most prominent prior studies from our perspective that have been able to overcome this data challange are those mentioned at the beginning, Souleles (2004) and Puri and Robinson (2007).

The paper by Souleles uses the panel dimension of the Michigan Survey of Consumer Attitudes and Behaviour (CAB) to measure consumers' expectations of how their financial situation develops and the subsequent realizations. Using these data, he shows that households' forecast errors are correlated with their demographics and thus that they are (ex post) biased. Besides assessing the

[5] To draw lines between the different strands in the literature is always a bit arbitrary. For example, there is a strand that examines macroeconomic expectations of households and their aggregate implications; see, e.g., Carroll (2003), Branch (2007), and Lanne, Luoma, and Luoto (2009). There is also a growing literature that links biased decision inputs (such as time-inconsistent / present-biased preferences) to subsequent economic and financial behaviour; see Ashraf, Karlan and Yin (2006) and Meir and Sprenger (2010) for prominent examples.

[6] It is important to note that this means that the data requirement for these studies are more stringent than that faced by the traditional studies that have focused on the accuracy of subjective expectations. To be able to study behavioral consequencies of expectational biases, one has to be able i) to measure how expectations differ from the subsequent realizations and then ii) to link the (potential) expectational errors to behavior or choices. See also Jappelli and Pistaferri (2010), who refer to the same challenge.

rationality of household expectations, Souleles evaluates whether the consumer sentiment and expectational questions of the CAB survey are useful in predicting household spending. Because the CAB survey provides limited data on spending, Souleles also uses data from the Consumer Expenditure Survey. When combined with a two-step, two-sample estimation strategy, this allows him to link the forecasts and forecast errors to household-level spending data. One of the most interesting findings that this strategy generates is that optimistic forecast errors (that is, negative innovations to income and financial position) are negatively related to consumption. Our analysis uses closely related measures of forecast errors, but unlike Souleles, we study household borrowing and can link the errors to it without an intermediate estimation step.

Puri and Robinson (2007) solve the data challenge in a different way. They use the Survey of Consumer Finance and a difference between self-reported life expectancy and statistical life tables to construct a measure of consumer optimism. Using this measure, they document that besides heterogeneity in the degree of optimism, there is a negative relation between holding extremely optimistic views and prudent choices, such as saving, long-term planning and non-smoking. We build directly on Puri and Robinson's analysis by making a distinction between moderate and large expectational errors. However, our analysis differs from theirs in two ways: On the one hand, we can construct a more direct measure for expectational errors and study how the errors are related to subsequent expectations formation. On the other hand, we focus on households' borrowing behaviour and overindebtedness, which is a domain that their analysis does not cover.[7]

Second, our paper is related to analyses of debt illiteracy, overindebtedness

[7] Puri and Robinson find, in particular, that their measure of optimism correlates positively with the balance payment habits of the U.S. credit card holders. To obtain this result, they use as a dependent variable a dummy that is equal to one if the respondent reports in a survey question that they pay their credit card balances in full.

and behavioral biases in the market for debt. Lusardi and Tufano (2009) emphasize the importance of low debt literacy for debt market outcomes: Those who appear to have a limited understanding of debt contracts and interest calculations pay more for their borrowing and are more like to be excessively indebted. Stango and Zinman (2009) provide related evidence. Their analysis focuses on the systematic tendency of consumers to underestimate loan interest rates (due to exponential growth bias). They use the Survey of Consumer Finance to demonstrate that this tendency matters empirically: Consumers who seem to suffer from it borrow more.

Other papers that document how behavioral mistakes and biases shape households' debt market behaviour include, but are not limited to, Yang, Markoczy and Qi (2007), Agarwal, Chomsisengphet, Liu and Souleles (2007), and Meier and Sprenger (2010), as well as those reviewed in Campbell et al. (2011). The last of these, for example, finds that present-biased consumers are more likely to have a credit card and, conditional on having (at least) one card, have higher revolving credit card balances. We add to this literature, as well as to that studying use of debt for consumption smoothing (e.g., Hurst and Stafford 2004, Sullivan 2008, Mian and Sufi 2011), by asking whether expectational biases matter and, in particular, how certain types of forecast errors are related to the level of indebtedness.

# 3 Data

Our main data source is Statistics Finland's Income Distribution Statistics (IDS). It is a nationally representative data set, covering private Finnish households and their members. The data set is annual and the sampling is based on a rotating panel: Each year, about half are new households; the rest have been included in the IDS once before. This rotation means that each household shows up in the data for two consecutive years.[8]

The IDS can be said to consist of two components: The first is a register-based component for which the data are collected from administrative registers, such as census data, tax registers, and social and pension registers. This register-based component of the data contains, for example, detailed demographic information about the households, as well as data on the sources of their income and borrowing behaviour. The second component of the IDS data comes from an interview-based database of Statistics Finland, called Income and Living Conditions Survey. This survey component includes, for example, questions about the expectations of households about the subsequent development of their financial situation.

As we explain in greater detail below, our empirical analysis relies on three important features of the IDS data: First, the survey component of the IDS data allows us to measure expectations. Second, the short panel aspect enables an empirical analysis of the subsequent realizations and, thereby, forecast errors. Third, the structure of the IDS data allows us link the forecast errors to households' borrowing behaviour.

The data we use cover years from 1994 to 2009. The initial annual IDS sample consists of about 10 000 households per year, but due to the timing of measurement of the expectations variables (see below), there are on average about four and half thousand households per year in our data. After allowing for some missing data and non-response to certain key questions, our baseline sample consists of 66 607 household-year observations.

We have matched to the IDS data a number of macroeconomic variables, such as the growth rate of gross domestic product (GDP), inflation, unemployment, stock and regional housing prices, and interest rates. The descriptive statistics of the IDS variables and macrovariables used in our empirical analysis

[8] The sampling scheme overweights entrepreneurs and high-income households.

are presented in Appendix A.

# 4 Measuring expectations and forecast errors

## 4.1 Expectations and realizations

To be able to quantify the nature and size of households' forecast errors (and their systematic expectational biases, if any), we need a measure for household $i$'s financial expectation for year $t$ and the subsequent realization. Our measures of these key quantities are based on the following two questions, asked in the survey component of the IDS:

Expectation, $E_{it|t-1}$, is derived from the first of the two surveys in which household $i$ participates. It is based on question "*How do you think that the financial situation of your household develops during the next 12 months (or during year t)?*". The following response categories are allowed: "*1 = is clearly better*", "*2 = is somewhat better*", "*3 = stays about the same*", "*4 = is somewhat worse*", and "*5 = is clearly worse*". The question refers to year $t$, but was asked in the survey that primarily concerns year $t-1$.

Actual outcome, $A_{it}$, is derived from the second of the two surveys (re-interview) in which $i$ participates. It is based on question "*How do you think that the financial situation of your household developed in year t?*". It allows the same response categories as the expectation question. The question refers to year $t$ and was asked in the survey that primarily deals with year $t$.[9]

We stress two aspects of these questions: First, the question on which $E_{it|t-1}$ is based asks about the future development of household $i$'s economic and financial position. Its wording and allowed categories match exactly with those of $A_{it}$, which measures the corresponding realization one year later. These questions

[9] Both questions also included categories "*don't want to say*" and "*don't know*". We however drop from the main analysis the households who did not answer to both questions on scale from 1 to 5.

are nearly identical to those used by Souleles (2004) to examine the development of the financial condition of U.S. households and the households' expectations about it (i.e., his variables $QFP^r$ and $QFP^e$). Like Souleles, we use the match between the two questions to analyse in-sample forecast errors at the level of households. Second, it is important to note that while households show up in the data for two consecutive periods, we can match $E_{it|t-1}$ with $A_{it}$ only for the latter period. This timing means, in particular, that we can compute only one forecast error per household. While this may sound restrictive at first, we can fortunately do so for a large number of households over a 15-year period.

Table 1 displays a cross-tabulation of $E_{it|t-1}$ and $A_{it}$. The entries are the number of observations falling in each cell and the associated cell probabilities. The table shows that a bit more than half of the observations in the data can be found from the diagonal cells, the sum of diagonal cell probabilities being 56.3%. Moreover, 35.2% of the observations are in the cells that are adjacent to the diagonal. These patterns indicate that expectations are strongly, but not perfectly, correlated with the subsequent outcomes.

[Insert Table 1 about here]

We can also infer from Table 1 that, on average, $A_{it}$ vary around $E_{it|t-1}$ symmetrically. Below the diagonal the sum of the cell probabilities is 22.0% and above it, the sum is 21.8%. These numbers are very close to each other, indicating that on average, the Finnish households have neither made optimistic nor pessimistic forecast errors over the sample period. The cell probabilities of the table also indicate that the fraction of households who appear to make large forecast errors (in either direction) is moderate but not negligible. For example, out of those who expect that their financial situation does not worsen (i.e., those for whom $E_{it|t-1} = 1, 2$ or 3), around 12.8% find that it actually worsens (i.e., $A_{it} = 4$ or 5).

### 4.2 Measuring forecast errors

The matched pair of questions, $E_{it|t-1}$ and $A_{it}$, allows us to calculate a forecast error for each household. We consider two complementary measures, which combine insights both from Souleles (2004) and Puri and Robinson (2007): Like Souleles, we use the difference between $E_{it|t-1}$ and $A_{it}$ as the basis of our forecast errors (see, e.g., his $\varepsilon FP$ measure). However, instead of just focusing on the absolute value of the difference, we follow Puri and Robinson and explicitly consider the *qualitative nature* of the forecast errors, such as whether the expectations and realizations imply mild or extreme optimism or non-prudent expectations formation.

Our first measure, denoted $FE1_{it}$, allows for 5 categories. They are clearly pessimistic forecast error ($FE1_{it} = 1$ if $A_{it} - E_{it|t-1} \leq -2$), moderately pessimistic forecast error ($FE1_{it} = 2$ if $A_{it} - E_{it|t-1} = -1$), no forecast error ($FE1_{it} = 3$ if $A_{it} - E_{it|t-1} = 0$), moderately optimistic forecast error ($FE1_{it} = 4$ if $A_{it} - E_{it|t-1} = 1$), and clearly optimistic forecast error ($FE1_{it} = 5$ if $A_{it} - E_{it|t-1} \geq 2$).

The logic of this measure is that it allows characterizing qualitatively whether the expectation of household $i$ about the development of its financial situation matches with its ex post view of the eventual realization. The optimistic (pessimistic) errors refer to the cases in which a household experiences a negative (positive) surprise relative to what it expected. For example, a household is said to make a clearly optimistic forecast error if it initially thought that its financial situation would clearly improve, but if it in the end stayed about the same or worsened. An example of a smaller optimistic error would be the case in which a household initially thought that its financial situation would improve somewhat, but in which it in the end stayed about the same.

It is also worth pointing out two features about the middle category ($FE1_{it} =$

3). First, it correponds to the case of the expectation matching with the subsequent perceived realization. When that is the case, a household can be said to have hold a realistic expectation of how its financial situation develops. Second, the measure is symmetric around the middle category: The error is allowed to be two-sided and of the "same magnitude" on the both sides of the middle category. That is, for each category on the pessimistic side there is a corresponding category on the optimistic forecast error side. We make use of this property when we study, e.g., whether households react symmetrically to forecast errors when forming an expectation for a subsequent period.

Our second measure, denoted $FE2_{it}$, is asymmetric and has four categories. Besides allowing for separate categories for those making pessimistic or no forecast errors, this measure distinguishes qualitatively between prudent and non-prudent optimistic errors. The categories of $FE2_{it}$ are pessimistic forecast error ($FE2_{it} = 1$ if $A_{it} - E_{it|t-1} < 0$), no forecast error ($FE2_{it} = 2$ if $A_{it} - E_{it|t-1} = 0$), prudentially optimistic forecast error ($FE2_{it} = 3$ if $A_{it} - E_{it|t-1} > 0$ and $A_{it} \leq 3$), and non-prudentially optimistic forecast error (if $A_{it} - E_{it|t-1} > 0$ and $A_{it} > 3$).

The prudentially optimistic forecast error refers to those cases in which a household experiences a negative surprise relative to what it expected but, despite of that happening, its financial situation does not actually worsen. A household is said to experience a non-prudent forecast error if it both experiences a negative surprise relative to what it expected and if its financial situation actually worsens.

Table 2 displays the distribution of the data by $FE1_{it}$ and $FE2_{it}$ and the average change in disposable income, measured in two alternative ways, for each forecast error category of the two measures (Panel A). It also displays the cross-tabulation of $FE1_{it}$ and $FE2_{it}$ (Panel B).

Reading Panel A, we can see that $FE1_{it}$ classifies 4.5% of the households as clearly optimistic and 17.2% as moderately optimistic. The corresponding numbers for the pessimistic errors are very close to these, 4.0% and 18.0%, respectively. The numbers for $FE2_{it}$, in turn, show that 12.0% of the households appear to make non-prudentially optimistic errors.

A particular worry about both $FE1_{it}$ and $FE2_{it}$ is that they are based on the subjective expectations and perceptions of households and thus that they do not measure anything real. However, Table 2 shows that the measures are not just noise: The second last column on the R.H.S. of Panel A shows, for example, that the average change in disposable annual income (from $t-1$ to $t$) declines monotonically as we go from the clearly pessimistic category ($FE1_{it} = 1$) to the clearly optimistic category ($FE1_{it} = 5$). This is what we would expect, if at least a part of the income change is unexpected or if households' expectations are at least partly inefficient ex ante. The last column on the R.H.S. of the panel shows that the same holds if we check how innovations in disposable income, as measured by a regression residual from an estimated AR(1) process (with year dummies included), vary across the forecast error categories. The last column shows, in particular, that those making optimistic errors experience, on average, negative income innovations. The only exception is the clearly pessimistic category, in which the change in income is a bit smaller (though still positive) than in the moderately pessimistic category. Finally, Panel A shows that also $FE2_{it}$ works as expected: households making non-prudentially optimistic forecast errors appear to be different from the rest: Their disposable income develops, on average, clearly less favorably. Their income declines about 2,100 EUR, whereas in the other categories, disposable income increases.

[Insert Table 2 about here]

Before proceeding, it is worth emphasizing that all the relations between our measures of forecast errors and household borrowing or indebtedness that we report subsequently are robust to conditioning on (changes in) household income. That is, the documented relations are not just due to households' borrowing behaviour adjusting to changes in their disposable income.

### 4.3 Understanding heterogeneity in forecast errors

What are the cross-sectional properties of forecast errors? How do they vary, for example, with demographics? To address these questions, we follow the lead of Souleles (2004) and Puri and Robinson (2007) and run regressions that relate forecast errors to the observable characteristics of households. We use $FE1_{it}$ and $FE2_{it}$ as the dependent variables in our regressions and model them using Ordered-probits (O-probit) and the repeated cross-sections IDS data from 1994 to 2009.

Compared to the prior work, our regressions come with two twists: The first twist is that we control flexibly for the cohort, age and time effects. The second twist is that we explicitly focus on the specific question of whether formal education is symmetrically associated with pessimistic and optimistic forecast errors. That is, are both types of errors increasing (or decreasing) with education? Or, does education have an asymmetric relation with them?

When studying the association of forecast errors with demographics and, particularly, education, there appears to be a number of reasons to control properly for the cohort, age and time effects. First, we ought to expect life cycle effects due to learning and aging: As the young become older, they learn and gain experience in forming forecasts. However, at some points in life, the marginal benefit of additional experience and cognitive skills begin to erode gradually. Second, people coming of age in different times have experienced different social and economic conditions (and, e.g., educational systems) in the past. Such generational differences show up as cohort effects in the forecast errors, if they, e.g., have influenced how individuals have learned to form expectations. This means, in particular, that the older generations do not necessarily provide a good image of the younger generations when they get older and, thus, that one cannot empirically distinguish between the age and cohort effects using data from a single cross-section. Third, as emphasized by Souleles (2004), overall economic conditions vary from year to year, giving raise to time effects in forecast errors.

Because controlling fully non-parametrically for all three effects simultaneously is not possible (see, e.g., Attanasio 1998 and Hall, Mairesse and Turner 2007), we proceed as follows:[10] First, we include long vectors of dummies for the cohort and age effects, which impose almost no restrictions on the life cycle (age) or generational (cohort) patterns in the data.[11] Second, we follow Gourinchas and Parker (2002) and model the time effects as a function of underlying macroeconomic and market condition variables. The set of variables that we use is unusually rich and include, for example, measures for real GDP growth, unemployment, inflation, stock returns and their variability, short interest rates and their variability. We also control for regional housing prices, which may boost home equity-based borrowing and consumption (Mian and Sudfi 2011).

Our motivation to focus on the association of forecast errors with education is two fold. First, the association is of intrinsic interest, as it can be indicative of education influencing how prone people are to make inefficient forecasts ex ante. It can also be indicative of certain educational categories suffering disproportionately from unfavorable shocks (e.g., due to unexpected skill-biased change). Second, the prior analyses of Souleles (2004) and Puri and Robinson (2007)

[10] Without a priori information or restrictions, there is no solution to the fundamental identification problem that is due to the fact that calendar year (time) is equal to the year of birth (cohort) plus age.

[11] In our baseline specifications, we have 20 age (running from the age of 19 to 79) and 20 cohort (running from year 1921 to 1981) dummies, which in both cases implies that a single dummy covers a period of three years. The results are robust to allowing for year-specific age or cohort dummies.

provide a somewhat mixed set of results on the relation between forecast errors and education. While not entirely conclusive, Souleles' (2004) results appear to suggest that people with low education are more likely to have made optimistic forecast errors. Puri and Robinson (2007) find, in contrast, that optimism is positively associated with better education.

To reassess how formal education is associated with forecast errors, we include separate dummies for secondary-level education, lower-degree tertiary education, higher-degree tertiary education, and doctoral education.[12] This results in a more flexible specification than that used in the preceding studies and allows a detailed look at how the various categories of education covary with forecast errors.

Table 3 reports the results from a series of O-probit regressions: In Panel A, the dependent variable is $FE1_{it}$, and in Panel B, it is $FE2_{it}$. Besides the cohort and age dummies and the macroeconomic and market condition variables mentioned above, the control variables in both panels include dummies for region of residence, socioeconomic status of the household, life-cycle stage of the household (as determined by the Statistics Finland), structure (type) of the household, marital status (of the head of the household), and dummies for the gender of household head and for those household heads who have just retired. The first column on the left does not control for household income. The second column includes a lagged disposable income (from period $t-1$), and the third column includes both the lagged income and a measure for innovations in disposable income, as measured by the regression residual from an estimated AR(1) process. Because our primary interest is in the association of education with forecast errors, we focus on the marginal effects of the education dummies, as reported in the lower parts of the panels; the marginal effect of the gender

[12] The omitted category include people with no or unknown education. The educational status refers to the respondent who in the survey identifies himself or herself as the head of household.

dummy is reported therein for comparison.

As can be seen from the table, having more education is negatively associated with optimistic forecast errors and positively associated with pessimistic forecast errors. The marginal effect due to a shift from no education to lower-degree tertiary education is about as large as the marginal effect of gender, which, in itself, indicates that males are less (more) likely to have made optimistic (pessimistic) forecast errors. When compared to the respective cell probabilities (see Panel A of Table 2) of the dependent variables, the moderating effects of better education are smaller in the category of moderately optimistic (pessimistic) errors than in the category of clearly optimistic (pessimistic) errors.

[Insert Table 3 about here]

As we see it, the above findings are quite in line with Souleles (2004) and sharpen the picture somewhat. They can be reconciled with two views: On the one hand, despite our extensive control vectors, we cannot rule out that people with better education have benefited disproportionately from favorable shocks, such as unexpected skill-biased technical change and the associated structural change in the business sector, that characterize the sample period. It is, however, important to note that, our results are robust not only to regional fixed effects and regional housing price development (which reflect structural change), but also to controlling for the past level of and unpredictable change in disposable income (as can be seen from the third columns of Table 3). This casts doubt on the proposition that the documented effects of education are solely due to a series of unexpected skill-biased income surprises (or equivalent ex post shocks). The alternative view of the above results is that getting more education has made people less prone to make (overly) optimistic forecasts ex ante.

# 5 Forecast errors and household borrowing behaviour

The findings in the earlier literature suggest that households that are prone to make forecast errors behave differently (Souleles 2004) and, perhaps, non-prudently (Puri and Robinson 2007). In this section, we aim at expanding the earlier analysis and focus on two main questions. First, do households who make forecast errors borrow more? In particular, are those making bigger forecast errors more indebted? Second, are error prone households more likely to report being overindebted?

## 5.1 Household borrowing and indebtedness

We study the relation of forecast errors with household borrowing and indebtedness in two ways. First, we make use of the fact that we have data on the total amount of outstanding loans that household $i$ has for two consecutive periods. The debt measure available in the IDS, $D_{it}$, is comprehensive, as it includes all household borrowing, including mortgages, consumer credit, student loans and loans taken up for the purpose of acquiring income. We can therefore calculate a change in the total amount of outstanding loans. In spirit of Sullivan (2008; see his eq. 1), this allows us to link the instantaneous behavioral response of household $i$ (i.e., whether it borrows more or pays back its debts) to forecast errors ($FE1_{it}$ and $FE2_{it}$). Second, we study the *level* of indebtedness and how it is related to $FE1_{it}$ and $FE2_{it}$.

Table 4 reports the results of OLS regressions of a change in $D_{it}$ on the category dummies that are formed on the basis of $FE1_{it}$ (Panel A) and $FE2_{it}$ (Panel B). In both panels, the specification underlying the first column includes no controls. The R.H.S. of the specification reported in the second column includes the age and cohort dummies, macroeconomic and market condition variables (the same as those used above), and the dummies for region of residence, socioeconomic status of the household, life-cycle stage of the household, structure (type) of the household, marital status, and dummies for educational achievement, gender of household head and for those household heads who have just retired. The third column includes, in addition, both the lagged income and the residual-based measure for innovations in disposable income.

The results of the two panels of the table show, perhaps a bit surprisingly, that those *not* making forecast errors borrow less (or pay more back their debts) than the households who make moderately pessimistic forecast errors. The estimates vary a bit across the columns, but in general, we cannot reject the null hypothesis that the coefficients of the pessimistic forecast error categories are *equal* to the corresponding coefficients of the optimistic forecast error categories. These results do not change materially even if we exclude from the estimating sample the households for whom the change in $D_{it}$ is zero.

The result is in line with the view that borrowing correlates with (unanticipated) income changes. It is harder to determine conclusively why the response to optimistic and pessimistic errors is similar: An interpretation of the symmetry that would be consistent with the standard consumption smoothing view is that the negative shocks, which lead to optimistic errors, are transitory and call for smoothing (via use of debt; Sullivan 2008) and that the positive shocks, which lead to pessimistic errors, are more permanent, and enhance households' borrowing capacity (see, e.g., Japelli and Pistaferri 2010). However, as we demonstrate below, other dimensions of our data suggest that this interpretation is problematic.

[Insert Table 4 about here]

To study household indebtedness, we divide $D_{it}$ by the disposable income of household $i$, calculated as the simple average of disposable income in $t-1$ and $t$ (i.e., over those two consecutive periods over which each household is observed in our data). This gives us a debt-to-income ratio, $D\_I_{it}$, which is a measure of how indebted a household is.

Table 5 reports both the OLS results and the marginal effects of Tobit regressions for models in which $D\_I_{it}$ is the dependent variable. The two panels give the results for $FE1_{it}$ (Panel A) and $FE2_{it}$ (Panel B), respectively, and the R.H.S. specifications of the three columns match exactly with those used in Table 4.

[Insert Table 5 about here]

Three main findings stand out from Panel A of the table: First, households that make optimistic forecast errors are more indebted than households who make no errors or who make pessimistic errors. This result is robust to scaling $D_{it}$ by the lagged income only (not reported) and to controlling for the past level of and unexpected change in disposable income (as can be seen from the third column of the table). Second, households that make clearly optimistic forecast errors are more indebted than those who make moderately optimistic errors. Third, the economic magnitudes are not negligible. For example, the mean $D\_I_{it}$ among those making clearly optimistic forecast errors is 0.14 higher than that of the households not making forecast errors. They thus have 0.14 cents more debt per each earned euro. The Tobit marginal effects show that this effect emerges because the households making clearly optimistic forecast errors are more likely to have debt and because conditional on having some debt, they have more of it.

Two further aspects about the above findings are worth noting. The first is that they square nicely with the results of Puri and Robinson (2007), who find that extreme, as opposed to moderate, optimism covaries positively with non-prudent economic behaviour. Our results suggest that the notion generalizes to other institutional environments and decision-making contexts and, in particular, to the market for household debt. The second thing to note is that our results are robust to controlling for the past level of and unexpected change in disposable income (as noted above). This aspect is important, as it suggests that the documented association of optimism with greater indebtedness is not just due to ex post income surprises. Moreover, the results are robust to controlling for regional housing prices, which suggest that the documented association cannot solely be explained by raising home prices and home equity-based borrowing (Mian and Sufi 2011).

Panel B shows that those making non-prudentially optimistic forecast errors do not differ significantly from those making prudentially optimistic forecast errors. However, households in both of these optimistic categories differ from households making pessimistic errors, because the latter are less indebted.

The above results are robust to a number of alternative specifications. First, the OLS results are robust to conditioning on $D\_I_{it} > 0$. Second, the results of a series of unreported quantile regressions show that households making optimistic forecast errors are more indebted than those making pessimistic forecast errors. This results suggests that the main findings of Table 5 are not due to outliers. Finally, the results remain intact if we replace $D\_I_{it}$ by a debt-payment-to-income ratio, which is defined here as the mortgage-service-to-income ratio (incl. both interest expenses and instalments) and which is a measure recently used by Johnson and Li (2010) to identify households that may face borrowing constraints. In particular, we find that households that make optimistic forecast errors have greater debt service ratios than the households who make no errors or who make pessimistic errors. Moreover, households that make clearly optimistic forecast errors have higher debt service ratios than those who make moderately optimistic errors. In sum, the alternative specifications echo our earlier results and support the view that greater optimism is associated with greater indebtedness.

## 5.2 Overindebtedness

Our results for household indebtedness suggest that extreme optimism, as captured in the above analysis by the category of clearly optimistic forecast errors, is positively related to greater debt burden. To take a closer look at what this means for the indebted households, we study how forecast errors covary with (self-reported) measures of overindebtedness. If the level of indebtedness of the households that make the largest optimistic forecast errors is alarmingly high, we would expect a positive relation between households making clearly optimistic forecast errors and indicators of overindebtedness. If there is such a relation it is likely to be related to non-prudent behavior in the market for debt.

There is unfortunately no agreement in the literature on what the overindebtedness of households means or how it should be measured. The standard model of consumption and intertemporal allocation (see, e.g., Attanasio and Weber 2010) predicts that households attempt to smooth their consumption intertemporally and that borrowing (or deleveraging) is an integral part of such smoothing (Sullivan 2008, Hurst and Stafford 2004). The possibility that households could carry suboptimal levels of (e.g. too much) debt is rarely explicitly considered.

In search of an established practise, we use as our primary dependent variable in this subsection a dummy that is equal to one if a household reports in the survey component of the IDS the perception that it has too much debt, and is zero otherwise. The measure is similar in spirit to that used by Lusardi and

Tufano (2009), but it is comforting to report already here that the results are not sensitive to this particular choice of the dependent variable (more on this below).

Table 6 reports the marginal effects of Logit regressions for models in which the dummy for the perceived overindebtedness is the dependent variable. The two panels give the results for $FE1_{it}$ (Panel A) and $FE2_{it}$ (Panel B), respectively, and the R.H.S. specifications of the three columns match, again, with those we used for Table 4.

[Insert Table 6 about here]

The results are robust across the columns of Table 6 and provide us with the key finding that households that make clearly optimistic forecast errors are more likely than others to report that they are overindebted. The result is asymmetric, as there is no corresponding effect on the pessimistic side. Interestingly, there is symmetry if we look at moderately pessimistic and optimistic errors: The marginal effects are of equal magnitude for the households who make such (smaller) forecast errors. The results reported for the households making non-prudentially optimistic forecast errors in Panel B confirm these findings. In sum, the results support the view that extreme optimism covaries positively with non-prudent, unsustainable levels of debt.

The results of Table 6 are robust to a number of alternative indicators of overindebtedness. First, the results are similar if we use as the dependent variable an indicator that is equal to one if a household reports (in the survey component of the IDS) that it has had to agree with its bank to reschedule its debt payments, and that is zero otherwise. Second, the results do no change if we use instead an indicator that is equal to one if a household reports that it has had problems in paying its regular (utility etc.) bills. Third, the results remain intact if the dependent variable is an indicator that is equal to one if a household reports that it has had problems in meeting its regular mortgage payments. Finally, the qualitative results are similar if the dependent variable is an indicator that is equal to one if a household has had to resort discretionary municipal supplementary benefits (i.e., social income assistance). Taken together, all these auxiliary analyses support the view that making large optimistic forecast errors covaries positively with unsustainable levels of debt.

# 6 Inattention and formation of expectations

In this section, we make use of the short panel aspect of the IDS data to examine how households update their financial expectations in the face of forecast errors. This analysis provides us with a way to examine whether there is something special in how those making optimistic forecast errors update their (financial) expectations. In spirit of the recent literature on consumer inattentiveness and following Reiss (2006), we focus on the possibility that those who make the largest optimistic forecast errors are less attentive to the errors than others when they form their expectations.

To this end, we use data on $E_{it|t-1}$ and $E_{it+1|t}$ and calculate a categorial variable that indicates whether, and if so how, household $i$ changes its expectation of its financial condition: The dependent variable that we use in this subsection takes value 3 if the household in the re-interview of the second survey qualitatively expects a better financial development during period $t+1$ than it did in the first survey for period $t$; it takes value 2 if there is no change in the expectation; and it takes value 1 if the household in the re-interview expects a worse development than it did in the first survey.[13]

[13] More formally, our measure for the change in expectations, $F\_ch_{it}$, allows for 3 categories as follows: $F\_ch_{it} = 3$ if $E_{it+1|t} - E_{it|t-1} < 0$, $F\_ch_{it} = 2$ if $E_{it+1|t} - E_{it|t-1} = 0$, and $F\_ch_{it} = 1$ if $E_{it+1|t} - E_{it|t-1} > 0$.

We run O-probit regressions which relate households' changes in their financial expectations (the dependent variable) to their (past) forecast errors, as measured by the categories of $FE1_{it}$ and $FE2_{it}$. Table 7 reports the marginal effects of these models. Panels A and B give the results for $FE1_{it}$ and $FE2_{it}$, respectively, and the R.H.S. specifications of the three columns in them match with those reported in Table 4.

The results of both panels show that households are not inattentive to past forecast errors. In particular, we find that the probability that a household expects a better (worse) development over the subsequent period than it did in the first survey is lower for the households for whom the forecast error indicates optimism (pessimism). This result is intuitive and consistent with households adjusting their expectations and reacting to past errors. However, adjustment is done in a surprising way: Households that make clearly optimistic errors update their expectations much less than those who make pessimistic forecast errors of similar magnitude. This means that adjustment is asymmetric.[14]

[Insert Table 7 about here]

There are at least two (not necessarily mutually exclusive) ways to interpret the asymmetry. First, some income shocks are (more) permanent whereas others are transitory, as the large literature on consumption responses to income changes suggests (Japelli and Pistaferri 2010). Our finding is consistent with rational updating if it is combined with the view that negative shocks, which lead to optimistic forecast errors, are less transitory than the positive shocks. The literature provides limited direct evidence on this, though there is some evidence, such as the documented (long-term) scarring effects of unemployment

[14] These results are robust to a number of alternative specifications. For example, if we use $E_{it+1|t}$ as the dependent variable (in place of the change in the expectation) and include the past expectation, i.e., $E_{it|t-1}$, as a control, the effects of the forecast errors remain qualitatively unchanged.

and job losses (see, e.g., Arulampalam, Booth and Taylor 2000, Gregg 2001, Huttunen, Møen, and Salvanes 2011) and the findings for the income effects of disability, which suggest the opposite. Second, the asymmetry in expectations adjustment that we find is consistent with the view that households are not sufficiently attentive (i.e., they underreact) to optimistic forecast errors.[15]

We cautiously lean on the latter interpretation, because the first is harder to reconcile with the other findings of this paper. Indeed, the asymmetry allows putting our results into a unifying context: First, it seems that households that make clearly optimistic errors believe that their forecast errors are less persistent and call for smaller expectational adjustments than the errors of those households that make pessimistic errors of similar magnitude. This asymmetry is consistent with the former being at risk of pursuing non-prudent borrowing behaviour and carrying greater levels of debt (e.g. not reducing debt). Over time, this kind of behaviour is likely to lead to undesired accumulation of debt.[16] Second, the finding of asymmetric adjustment is in line with the view that households who make clearly optimistic forecast errors are more likely than others to report that they are overindebted. Such reports square with the view that some households adjust their expectations systematically too little, leading - perhaps gradually - to excessive debt loads. [17]

[15] Of course, the finding is also in line with the view that households overweight their recent forecast errors on the pessimistic side. While we cannot study this further, this would probably lead to a subsequent optimistic forecast error.

[16] This view is *not* consistent with the standard consumption smoothing view (that we mentioned earlier).

[17] We admit that this suggested chain of events is hard to study formally using our data. However, subsequent work with longer panels can test the conjecture that households making repeated optimistic forecast errors accumulate too much debt over time and are therefore more likely than others to subsequently report that they are overindebted.

# 7 Conclusions

While the view that households may be subject to behavioural biases and have limited cognitive capacity to make optimal borrowing decisions is not new (see Campbell et al. 2011 for a recent review), we think that taken together, the findings of this paper portray a novel picture of optimism in the market for household debt: Households that make clearly optimistic errors apparently believe that their forecast errors call for smaller expectational adjustments than the errors of those households that make pessimistic errors of similar magnitude. This asymmetry in the adjustment of expectations is consistent with the former being at risk of accumulating greater, imprudent levels of debt. This process is a potential explanation for the finding that households who make clearly optimistic errors are most likely to report that they are overindebted.

Behavioral consequences and sources of household optimism and forecast errors are not yet well-understood. Our analysis is a first step only, as their complete characterization calls for more detailed data than appears to be currently available. We hope, however, that we have laid ground for subsequent research efforts in this domain. Can similar asymmetric patterns in expectations adjustment and overindebtedness, as reported here, be found in other forecasting contexts and environments? Is household optimism persistent? Can it be linked to the findings which suggest that households react to predictable changes in disposable income (Coulibaly and Li 2006; see also Stephens 2008), which is inconsistent with the standard permanent income hypothesis (Jappelli and Pistaferri 2010)? Finally, are there spillover effects of household forecast errors? For example, how should we interpret the effects of debt on household portfolio choices (Becker and Shabani 2010) or default-prone home equity-based borrowing (Mian and Sufi 2011), if the level of indebtedness is in part - or at least for some - driven be expectational errors or biases?

## References


[1] Agarwal, S, Chomsisengphet, S., Liu, C. and Souleles N. S. (2007), Do consumers choose the right credit contracts? University of Pennsylvania, manuscript.

[2] Alessie, R. and Lusardi, A. (1997),Saving and income smoothing: Evidence from panel data, *European Economic Review*, Vol. 41, No. 7, pp. 1251-1279.

[3] Arulampalam, W., Booth, A.L., Taylor, M.P. (2000), Unemployment persistence, *Oxford Economic Papers*, Vol. 52, pp. 24-50.

[4] Asharf, N., Karlan D., and Yin, W. (2006), Tying Odysseus to the mast: Evidence from a commitment savings product in the Philippines, *Quarterly Journal of Economics*, Vol. 121, pp. 635-672.

[5] Attanasio, O. P. (1998), Cohort analysis of saving behaviour by U.S. households, *Journal of Human Resources*, Vol. 33, No. 3, pp. 575-609.

[6] Attanasio, O. P. and Weber, G. (2010), Consumption and saving: Models of intertemporal allocation and their implications for public policy, *Journal of Economic Literature*, Vol. 48, pp. 693-751.

[7] Becker, T. A. and Shabani, R. (2010), Outstanding debt and the household portfolio, *Review of Financial Studies*, Vol. 23, No. 7, pp. 2900-2934.

[8] Branch, W. A. (2007), Sticky information and model uncertainty in survey data on inflation expectations, *Journal of Economic Dynamics and Control*, Vol. 31, pp. 245-276.

[9] Campbell, J. Y., Jackson, H. E., Madrian, B. C. and Tufano, P. (2011), Consumer financial protection, *Journal of Economic Perspectives*, Vol. 25, No. 1, pp. 91-114.

[10] Carroll, C. (2003), Macroeconomic expectations of households and professional forecasters, *Quarterly Journal of Economics*, Vol. 118, pp. 269-298.

[11] Coulibaly, B. and Li, G. (2006), Do homeowners increase consumption after the last mortgage payment? An alternative test of the permanent income hypothesis, *Review of Economics and Statistics*, Vol. 88, No. 1, pp. 10-19.

[12] Das, M. and van Soest, A. (1999), A panel data model for subjective information on household income growth, *Journal of Economic Behaviour and Organization*, Vol. 40, pp. 409-426.

[13] Dominitz, J. (1998), Earnings, expectations, revisions, and realizations, *Review of Economics and Statistics*, Vol. 82, pp. 374-388.

[14] Gourinchas, P-O. and Parker, J. A. (2002), Consumption over the life cycle, *Econometrica*, Vol. 70, No. 1, pp. 47-89.

[15] Gregg, P. (2001), The impact of youth unemployment on adult unemployment in the NCDS, *Economic Journal*, Vol. 111 (475), pp. 626-653.

[16] Hall, B. H., Mairesse, J. and Turner, L. (2007), Identifying age, cohort, and period effects in scientific research productivity: Discussion and illustration using simulated and actual data on French physicists, *Economics of Innovation and New Technology*, Vol. 16, No. 2, pp. 159-177.

[17] Hayashi F. (1985), The permanent income hypothesis and consumption durability; estimates from panel data on households, *Quarterly Journal of Economics*, Vol. 100, pp. 1083-1113.

[18] Hurst, E. and Stafford, F. (2004), Home is where equity is: Mortgage refinancing and household consumption, *Journal of Money, Credit and Banking*, Vol. 36, No. 6, pp. 985-1014.

[19] Huttunen, K., Møen, J., Salvanes, K.G. (2011), How destructive is creative destruction? Effects of job loss on mobility, withdrawal and income, *Journal of the European Economic Association*, Vol. 9, pp. 840-870.

[20] Inderst, R. (2008), ´Irresponsible lending' with a better informed lender, *Economic Journal*, Vol. 118, pp. 1499-1519.

[21] Jappelli, T. and Pistaferri, L. (2010), The consumption response to income changes, *Annual Review of Economics*, Vol. 2, pp. 479-506.

[22] Johnson, K. W. and Li, G. (2010), The debt-payment-to-income ratio as an indicator of borrowing constraints: Evidence from two household surveys, *Journal of Money, Credit and Banking*, Vol. 42, No. 7, pp. 1373-1390.

[23] Lanne, M., Luoma, A. and Luoto, J. (2009), A naive sticky information model of households' inflation expectations, *Journal of Economic Dynamics and Control*, Vol. 33, pp. 1332-1344.

[24] Lusardi, A. and Tufano, P. (2009), Debt literacy, financial experiences, and overindebtedness, mimeo, Dartmouth College.

[25] Kaufmann, K. and Pistaferri, L. (2009), Disentangling insurance and information in intertemporal consumption choices, *American economic Review, Paper and Proceedings*, Vol. 99, No. 2, pp. 387-392.

[26] Manski, C. (2004), Measuring expectations, *Econometrica*, Vol. 72, No. 5, pp. 1329-1376.

[27] Mian, A. and Sufi, A. (2011), House prices, home equity-based borrowing, and the U.S. household leverage crisis, *American Economic Review*, Vol. 101, pp. 2132-2156.

[28] Meier, S. and Sprenger, C. (2010), Present-biased preferences and credit card borrowing, *American Economic Journal: Applied Economics*, Vol. 2, No. 1, pp. 193-210.

[29] Moore, D. A. and Healy P. J. (2008), The trouble with overconfidence, *Psychological Review*, Vol. 115, No. 2, pp. 502-517.

[30] Pistaferri, L. (2001), Superior information, income shocks, and the permanent income hypothesis, *Review of Economics and Statistics*, Vol. 83, pp. 465-476.

[31] Puri, M. and Robinson, D. (2007), Optimism and economic choice, *Journal of Financial Economics*, Vol. 86, pp. 71-99.

[32] Reiss, R. (2006), Inattentive consumers, *Journal of Monetary Economics*, Vol. 53, pp. 1761-1800.

[33] Souleles, N. S. (2004), Expectations, heterogenous forecast errors and consumption: Micro evidence from the Michigan Consumer Sentiment Surveys, *Journal of Money, Credit and Banking*, Vol. 36, No. 1, pp. 39-72.

[34] Stango, V. and Zinman, J. (2009), Exponential growth bias and household finance, *Journal of Finance*, Vol. 64, pp. 2807-2849.

[35] Stephens, M. Jr. (2008), The consumption response to predictable changes in discreationary income: Evidence from the repayment of vehicle loans, *Review of Economics and Statistics*, Vol. 90, No. 2, pp. 241-252.

[36] Sullivan, J. X. (2008), Borrowing during unemployment: Unsecured debt as a safety net, *Journal of Human Resources*, Vol. 43, pp. 383-412.

[37] Zeldes, P. (1989) Consumption and liquidity constraints: An empirical investigation, *Journal of Political Economy*, Vol. 97, pp. 305-346.

[38] Yang, S., Markoczy, L. and Qi, M. (2007), Unrealistic optimism in consumer credit card adoption, *Journal of Economic Psychology*, Vol. 28, pp. 170-185.

**Table 1**: Cross-tabulation of expectations and actual outcomes

This table reports the cross-tabulation of households' expectations ($E_{it|t-1}$) on the development of their financial situation over the next 12 months (year t) and the actual outcomes ($A_{it}$), as assessed a year later. The categories take on values "1 = clearly towards better", "2 = somewhat towards better", "3 = stays/stayed about the same", "4 = somewhat towards worse", and "5 = clearly towards worse". The cell entries are the number of households and the corresponding cell probabilities. The data are from the Statistics Finland's Income Distribution Statistics (1994–2009).

| | Actual outcome ($A_{it}$) | | | | | |
|---|---|---|---|---|---|---|
| Expectation ($E_{it\|t-1}$) | 1 | 2 | 3 | 4 | 5 | Total |
| 1 | 567 | 794 | 426 | 110 | 63 | 1,960 |
| | 0.9 % | 1.2 % | 0.6 % | 0.2 % | 0.1 % | 2.9 % |
| 2 | 906 | 5,518 | 5,263 | 1,104 | 335 | 13,126 |
| | 1.4 % | 8.3 % | 7.9 % | 1.7 % | 0.5 % | 19.7 % |
| 3 | 694 | 6,554 | 28,147 | 4,595 | 987 | 40,977 |
| | 1.0 % | 9.8 % | 42.3 % | 6.9 % | 1.5 % | 61.5 % |
| 4 | 85 | 911 | 3,872 | 2,602 | 812 | 8,282 |
| | 0.1 % | 1.4 % | 5.8 % | 3.9 % | 1.2 % | 12.4 % |
| 5 | 34 | 216 | 718 | 652 | 642 | 2,262 |
| | 0.1 % | 0.3 % | 1.1 % | 1.0 % | 1.0 % | 3.4 % |
| Total | 2,286 | 13,993 | 38,426 | 9,063 | 2,839 | 66,607 |
| | 3.4 % | 21.0 % | 57.7 % | 13.6 % | 4.3 % | 100.0 % |

**Table 2**: Distribution and cross-tabulation of forecast errors

Panel A reports the distribution of the data by the forecast error categories and average changes in disposable income for each category. The change in disposable income is measured in two alternative ways: by the annual change in the disposable income and by the innovation in the income, as measured by the residual of the regression of income on lagged income and year dummies. Panel B reports the cross-tabulation of the two forecast error measures ($FE1_{it}$ and $FE2_{it}$). The data are from the Statistics Finland's Income Distribution Statistics (1994–2009).

Panel A: Distribution of the forecast errors and changes in income by the error category

| | Obs. | Percent | Cum. | Change in income | Innovation in income |
|---|---|---|---|---|---|
| $FE1_{it}$ | | | | | |
| Clearly pessimistic | 2,658 | 4.0 % | 4.0 % | 1.767 | 0.602 |
| Moderately pessimistic | 11,984 | 18.0 % | 22.0 % | 1.629 | 1.233 |
| None | 37,476 | 56.3 % | 78.3 % | 1.159 | 0.247 |
| Moderately optimistic | 11,464 | 17.2 % | 95.5 % | 0.094 | -1.118 |
| Clearly optimistic | 3,025 | 4.5 % | 100.0 % | -2.095 | -4.238 |
| Total | 66,607 | 100.0 % | | | |
| $FE2_{it}$ | | | | | |
| Pessimistic | 14,642 | 22.0 % | 22.0 % | 1.654 | 1.119 |
| None | 37,476 | 56.3 % | 78.3 % | 1.159 | 0.247 |
| Prudentially optimistic | 6,483 | 9.7 % | 88.0 % | 1.796 | 0.952 |
| Non-prudentially optimistic | 8,006 | 12.0 % | 100.0 % | -2.112 | -3.972 |
| Total | 66,607 | 100.0 % | | | |

Panel B: Cross-tabulation of forecast error measures ($FE1_{it}$ and $FE2_{it}$)

| | $FE2_{it}$ | | | | |
|---|---|---|---|---|---|
| $FE1_{it}$ | Pessimistic | None | Prudentially optimistic | Non-prudentially optimistic | Total |
| Clearly pessimistic | 2,658 | - | - | - | 2,658 |
| | 4.0 % | - | - | - | 4.0 % |
| Moderately pessimistic | 11,984 | - | - | - | 11,984 |
| | 18.0 % | - | - | - | 18.0 % |
| None | - | 37,476 | - | - | 37,476 |
| | - | 56.3 % | - | - | 56.3 % |
| Moderately optimistic | - | - | 6,057 | 5,407 | 11,464 |
| | - | - | 9.1 % | 8.1 % | 17.2 % |
| Clearly optimistic | - | - | 426 | 2,599 | 3,025 |
| | - | - | 0.6 % | 3.9 % | 4.5 % |
| Total | 14,642 | 37,476 | 6,483 | 8,006 | 66,607 |
| | 22.0 % | 56.3 % | 9.7 % | 12.0 % | 100.0 % |

**Table 3**: Determinants of forecast errors

This table reports coefficient estimates and average marginal effects of education and gender from Ordered probit models in which the dependent variable is forecast error $FE1_{it}$ (Panel A) and $FE2_{it}$ (Panel B). The forecast errors measured by FE1 take on values "1 = clearly pessimistic", "2 = moderately pessimistic", "3 = no error", "4 = moderately optimistic", and "5 = clearly optimistic". The forecast errors measured by FE2 take on values"1 = pessimistic", "2 = no error", "3 = prudentially optimistic", and "4 = non-prudentially optimistic". Standard errors are clustered at the region-year level and reported in parentheses; *** $p<0.001$, ** $p<0.01$, * $p<0.05$. The data are from the Statistics Finland's Income Distribution Statistics (1994–2009).

Panel A: Dependent variable $FE1_{it}$

| Ordered probit estimates | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| Secondary-level education | -0.023* | -0.021 | -0.019 |
| | (0.011) | (0.011) | (0.011) |
| Lower-degree tertiary education | -0.033* | -0.029* | -0.022 |
| | (0.014) | (0.014) | (0.015) |
| Higher-degree tertiary education | -0.076*** | -0.068*** | -0.051** |
| | (0.018) | (0.018) | (0.018) |
| Doctoral education | -0.093** | -0.083* | -0.059 |
| | (0.035) | (0.036) | (0.036) |
| Male | -0.034*** | -0.033** | -0.026* |
| | (0.010) | (0.010) | (0.010) |
| Demographic control variables | Yes | Yes | Yes |
| Macroeconomic variables | Yes | Yes | Yes |
| Lagged income | No | Yes | Yes |
| Income surprise | No | No | Yes |
| | | | |
| N | 66,607 | 66,607 | 66,607 |
| Pseudo R-squared | 0.003 | 0.003 | 0.004 |
| p-value for LR-test of coefficients = 0 | | | |
| Macro variables | <0.001 | <0.001 | <0.001 |
| Socioeconomic status | <0.001 | <0.001 | <0.001 |
| Region of residence | 0.003 | 0.002 | 0.001 |
| Cohort | 0.217 | 0.196 | 0.166 |
| Age group | <0.001 | <0.001 | <0.001 |

| Average marginal effects | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| | Clearly pessimistic forecast error | | |
| Secondary-level education | 0.002* | 0.002* | 0.002 |
| | (0.001) | (0.001) | (0.001) |
| Lower-degree tertiary education | 0.003* | 0.003* | 0.002* |
| | (0.001) | (0.001) | (0.001) |
| Higher-degree tertiary education | 0.007*** | 0.007*** | 0.006*** |
| | (0.002) | (0.002) | (0.002) |
| Doctoral education | 0.008** | 0.008** | 0.007* |
| | (0.003) | (0.003) | (0.003) |
| Male | 0.003*** | 0.003*** | 0.003** |
| | (0.001) | (0.001) | (0.001) |
| | Moderately pessimistic forecast error | | |
| Secondary-level education | 0.005* | 0.005* | 0.004 |
| | (0.002) | (0.002) | (0.002) |
| Lower-degree tertiary education | 0.007* | 0.007* | 0.006* |
| | (0.003) | (0.003) | (0.003) |
| Higher-degree tertiary education | 0.016*** | 0.016*** | 0.014*** |
| | (0.004) | (0.004) | (0.004) |
| Doctoral education | 0.020** | 0.020** | 0.017* |
| | (0.008) | (0.008) | (0.008) |
| Male | 0.007*** | 0.007*** | 0.007** |
| | (0.002) | (0.002) | (0.002) |
| | Moderately optimistic forecast error | | |
| Secondary-level education | -0.005* | -0.005* | -0.004 |
| | (0.002) | (0.002) | (0.002) |
| Lower-degree tertiary education | -0.006* | -0.006* | -0.006* |
| | (0.003) | (0.003) | (0.003) |
| Higher-degree tertiary education | -0.015*** | -0.015*** | -0.013*** |
| | (0.003) | (0.003) | (0.004) |
| Doctoral education | -0.018** | -0.018** | -0.016* |
| | (0.007) | (0.007) | (0.007) |
| Male | -0.007*** | -0.007*** | -0.006** |
| | (0.002) | (0.002) | (0.002) |
| | Clearly optimistic forecast error | | |
| Secondary-level education | -0.002* | -0.002* | -0.002 |
| | (0.001) | (0.001) | (0.001) |
| Lower-degree tertiary education | -0.003* | -0.003* | -0.003* |
| | (0.001) | (0.001) | (0.001) |
| Higher-degree tertiary education | -0.007*** | -0.007*** | -0.006*** |
| | (0.002) | (0.002) | (0.002) |
| Doctoral education | -0.008** | -0.008** | -0.008* |
| | (0.003) | (0.003) | (0.003) |
| Male | -0.003*** | -0.003*** | -0.003** |
| | (0.001) | (0.001) | (0.001) |

Panel B: Dependent variable $FE2_{it}$

| Ordered probit estimates | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| Secondary-level education | -0.026* | -0.024* | -0.021 |
| | (0.012) | (0.012) | (0.012) |
| Lower-degree tertiary education | -0.041** | -0.037* | -0.029 |
| | (0.014) | (0.015) | (0.015) |
| Higher-degree tertiary education | -0.083*** | -0.074*** | -0.054** |
| | (0.018) | (0.019) | (0.019) |
| Doctoral education | -0.100** | -0.088* | -0.063 |
| | (0.036) | (0.037) | (0.038) |
| Male | -0.045*** | -0.044*** | -0.037*** |
| | (0.010) | (0.010) | (0.010) |
| Demographic control variables | Yes | Yes | Yes |
| Macroeconomic variables | Yes | Yes | Yes |
| Lagged income | No | Yes | Yes |
| Income surprise | No | No | Yes |
| | | | |
| N | 66,607 | 66,607 | 66,607 |
| Pseudo R-squared | 0.003 | 0.003 | 0.004 |
| p-value for LR-test of coefficients = 0 | | | |
| Macro variables | <0.001 | <0.001 | <0.001 |
| Socioeconomic status | <0.001 | <0.001 | <0.001 |
| Region of residence | 0.002 | 0.002 | 0.001 |
| Cohort | 0.396 | 0.374 | 0.345 |
| Age group | <0.001 | <0.001 | <0.001 |

| Average marginal effects | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| | | Pessimistic | |
| Secondary-level education | 0.008* | 0.007* | 0.006 |
| | (0.003) | (0.003) | (0.003) |
| Lower-degree tertiary education | 0.012** | 0.011* | 0.008 |
| | (0.004) | (0.004) | (0.004) |
| Higher-degree tertiary education | 0.025*** | 0.022*** | 0.016** |
| | (0.006) | (0.006) | (0.006) |
| Doctoral education | 0.030** | 0.026* | 0.019 |
| | (0.011) | (0.011) | (0.011) |
| Male | 0.013*** | 0.013*** | 0.011*** |
| | (0.003) | (0.003) | (0.003) |
| | | Prudentially optimistic | |
| Secondary-level education | -0.002* | -0.002* | -0.002 |
| | (0.001) | (0.001) | (0.001) |
| Lower-degree tertiary education | -0.004** | -0.003* | -0.003 |
| | (0.001) | (0.001) | (0.001) |
| Higher-degree tertiary education | -0.008*** | -0.007*** | -0.005** |
| | (0.002) | (0.002) | (0.002) |
| Doctoral education | -0.009** | -0.008* | -0.006 |
| | (0.003) | (0.004) | (0.004) |
| Male | -0.004*** | -0.004*** | -0.003*** |
| | (0.001) | (0.001) | (0.001) |
| | | Non-prudentially optimistic | |
| Secondary-level education | -0.005* | -0.005* | -0.004 |
| | (0.002) | (0.002) | (0.002) |
| Lower-degree tertiary education | -0.008** | -0.007* | -0.006 |
| | (0.003) | (0.003) | (0.003) |
| Higher-degree tertiary education | -0.016*** | -0.014*** | -0.011** |
| | (0.004) | (0.004) | (0.004) |
| Doctoral education | -0.019** | -0.017* | -0.012 |
| | (0.007) | (0.007) | (0.007) |
| Male | -0.009*** | -0.009*** | -0.007*** |
| | (0.002) | (0.002) | (0.002) |

**Table 4**: Forecast errors and borrowing

Panels A and B report OLS estimates of the effect of forecast errors ($FE1_{it}$ and $FE2_{it}$, respectively) on changes in the stock of debt. Standard errors are clustered at the region-year level and reported in parentheses; *** p<0.001, ** p<0.01, * p<0.05. The data are from the Statistics Finland's Income Distribution Statistics (1994–2009).

| Panel A: FE1 and change in stock of debt | | | |
|---|---|---|---|
| | Model 1 | Model 2 | Model 3 |
| Clearly pessimistic | 0.873 | 0.762 | 0.740 |
| | (0.486) | (0.481) | (0.482) |
| Moderately pessimistic | 0.644*** | 0.469* | 0.457* |
| | (0.193) | (0.185) | (0.186) |
| Moderately optimistic | 0.603** | 0.431 | 0.466* |
| | (0.232) | (0.226) | (0.225) |
| Clearly optimistic | 0.191 | 0.016 | 0.107 |
| | (0.380) | (0.383) | (0.379) |
| Demographic control variables | No | Yes | Yes |
| Macroeconomic variables | No | Yes | Yes |
| Lagged income and income surprise | No | No | Yes |
| | | | |
| N | 66,607 | 66,607 | 66,607 |
| R-squared | 0.000 | 0.018 | 0.019 |
| p-value for F-test of equality of coefficients | | | |
| Clearly optimistic vs. clearly pessimistic | 0.222 | 0.180 | 0.252 |
| Clearly optimistic vs. moderately optimistic | 0.312 | 0.314 | 0.381 |
| Clearly pessimistic vs. moderately pessimistic | 0.635 | 0.541 | 0.556 |
| Moderately optimistic vs. moderarately pessimistic | 0.878 | 0.886 | 0.974 |

| Panel B: FE2 and change in stock of debt | | | |
|---|---|---|---|
| | Model 1 | Model 2 | Model 3 |
| Pessimistic | 0.686*** | 0.521** | 0.508** |
| | (0.197) | (0.190) | (0.190) |
| Prudentially optimistic | 0.784* | 0.250 | 0.249 |
| | (0.323) | (0.324) | (0.324) |
| Non-prudentially optimistic | 0.300 | 0.421 | 0.506* |
| | (0.243) | (0.237) | (0.233) |
| Demographic control variables | No | Yes | Yes |
| Macroeconomic variables | No | Yes | Yes |
| Lagged income and income surprise | No | No | Yes |
| | | | |
| N | 66,607 | 66,607 | 66,607 |
| R-squared | 0.000 | 0.018 | 0.019 |
| p-value for F-test of equality of coefficients | | | |
| Non-prudentially optimistic vs. pessimistic | 0.162 | 0.711 | 0.994 |
| Prudentially optimistic vs. pessimistic | 0.774 | 0.427 | 0.450 |
| Non-prudentially optimistic vs. prudentially optimistic | 0.194 | 0.649 | 0.494 |

**Table 5**: Forecast errors and indebtedness

Panels A and B report OLS estimates of the effect of forecast errors ($FE1_{it}$ and $FE2_{it}$, respectively) on the debt-to-income ratio and the marginal effects from the corresponding Tobit models. Standard errors are clustered at the region-year level and reported in parentheses; *** $p<0.001$, ** $p<0.01$, * $p<0.05$. The data are from the Statistics Finland's Income Distribution Statistics (1994–2009).

Panel A: FE1 and debt-to-income ratio

| OLS estimates | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| Clearly pessimistic | 0.148*** | 0.033 | 0.032 |
| | (0.019) | (0.019) | (0.019) |
| Moderately pessimistic | 0.111*** | 0.023** | 0.023** |
| | (0.011) | (0.008) | (0.008) |
| Moderately optimistic | 0.194*** | 0.097*** | 0.095*** |
| | (0.012) | (0.010) | (0.010) |
| Clearly optimistic | 0.290*** | 0.145*** | 0.142*** |
| | (0.022) | (0.020) | (0.020) |
| Demographic control variables | No | Yes | Yes |
| Macroeconomic variables | No | Yes | Yes |
| Lagged income and income surprise | No | No | Yes |
| | | | |
| N | 66,607 | 66,607 | 66,607 |
| R-squared | 0.008 | 0.225 | 0.227 |
| p-value for F-test of equality of coefficients | | | |
| Clearly optimistic vs. clearly pessimistic | 0.000 | 0.000 | 0.000 |
| Clearly optimistic vs. moderately optimistic | 0.000 | 0.021 | 0.026 |
| Clearly pessimistic vs. moderately pessimistic | 0.119 | 0.634 | 0.652 |
| Moderately optimistic vs. moderarately pessimistic | 0.000 | 0.000 | 0.000 |

| Tobit average marginal effects | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| | Expected value conditional on being indebted | | |
| Clearly pessimistic | 0.110*** | 0.024* | 0.024* |
| | (0.012) | (0.011) | (0.011) |
| Moderately pessimistic | 0.094*** | 0.028*** | 0.028*** |
| | (0.007) | (0.005) | (0.005) |
| Moderately optimistic | 0.141*** | 0.076*** | 0.076*** |
| | (0.007) | (0.006) | (0.006) |
| Clearly optimistic | 0.206*** | 0.111*** | 0.110*** |
| | (0.012) | (0.011) | (0.011) |
| | Probability of being indebted | | |
| Clearly pessimistic | 0.076*** | 0.015* | 0.015* |
| | (0.008) | (0.007) | (0.007) |
| Moderately pessimistic | 0.065*** | 0.018*** | 0.018*** |
| | (0.004) | (0.003) | (0.003) |
| Moderately optimistic | 0.098*** | 0.048*** | 0.047*** |
| | (0.005) | (0.004) | (0.004) |
| Clearly optimistic | 0.142*** | 0.070*** | 0.069*** |
| | (0.008) | (0.007) | (0.007) |

| Panel B: FE2 and debt-to-income ratio | | | |
|---|---|---|---|
| OLS estimates | Model 1 | Model 2 | Model 3 |
| Pessimistic | 0.118*** | 0.024** | 0.025** |
| | (0.009) | (0.008) | (0.008) |
| Prudentially optimistic | 0.285*** | 0.111*** | 0.110*** |
| | (0.016) | (0.013) | (0.013) |
| Non-prudentially optimistic | 0.155*** | 0.103*** | 0.100*** |
| | (0.014) | (0.013) | (0.013) |
| Demographic control variables | No | Yes | Yes |
| Macroeconomic variables | No | Yes | Yes |
| Lagged income and income surprise | No | No | Yes |
| | | | |
| N | 66,607 | 66,607 | 66,607 |
| R-squared | 0.009 | 0.224 | 0.227 |
| p-value for F-test of equality of coefficients | | | |
| Non-prudentially optimistic vs. pessimistic | 0.013 | 0.000 | 0.000 |
| Prudentially optimistic vs. pessimistic | 0.000 | 0.000 | 0.000 |
| Non-prudentially optimistic vs. prudentially optimistic | 0.000 | 0.625 | 0.576 |
| Tobit average marginal effects | Model 1 | Model 2 | Model 3 |
| | Expected value conditional on being indebted | | |
| Pessimistic | 0.097*** | 0.027*** | 0.028*** |
| | (0.006) | (0.005) | (0.005) |
| Prudentially optimistic | 0.208*** | 0.087*** | 0.086*** |
| | (0.009) | (0.008) | (0.008) |
| Non-prudentially optimistic | 0.110*** | 0.081*** | 0.080*** |
| | (0.008) | (0.008) | (0.008) |
| | Probability of being indebted | | |
| Pessimistic | 0.067*** | 0.017*** | 0.017*** |
| | (0.004) | (0.003) | (0.003) |
| Prudentially optimistic | 0.144*** | 0.054*** | 0.054*** |
| | (0.006) | (0.005) | (0.005) |
| Non-prudentially optimistic | 0.076*** | 0.051*** | 0.050*** |
| | (0.005) | (0.005) | (0.005) |

**Table 6**: Forecast errors and overindebtedness

Panels A and B report Logit marginal effects of forecast errors ($FE1_{it}$ and $FE2_{it}$, respectively) on perceived overindebtedness. Standard errors are clustered at the region-year level and reported in parentheses; *** p<0.001, ** p<0.01, * p<0.05. The data are from the Statistics Finland's Income Distribution Statistics (1996–2009).

| Panel A: FE1 and perceived overindebtedness | | | |
|---|---|---|---|
| Logit average marginal effects | Model 1 | Model 2 | Model 3 |
| Clearly pessimistic | 0.025*** | 0.017** | 0.015** |
| | (0.006) | (0.006) | (0.005) |
| Moderately pessimistic | -0.001 | -0.003 | -0.002 |
| | (0.004) | (0.003) | (0.003) |
| Moderately optimistic | 0.032*** | 0.027*** | 0.025*** |
| | (0.003) | (0.003) | (0.003) |
| Clearly optimistic | 0.078*** | 0.066*** | 0.060*** |
| | (0.004) | (0.003) | (0.003) |
| Demographic control variables | No | Yes | Yes |
| Macroeconomic variables | No | Yes | Yes |
| Lagged income and income surprise | No | No | Yes |
| N | 32,248 | 32,248 | 32,248 |

| Panel B: FE2 and perceived overindebtedness | | | |
|---|---|---|---|
| Logit average marginal effects | Model 1 | Model 2 | Model 3 |
| Pessimistic | 0.004 | 0.002 | 0.002 |
| | (0.003) | (0.003) | (0.003) |
| Prudentially optimistic | 0.013** | 0.008* | 0.008 |
| | (0.004) | (0.004) | (0.004) |
| Non-prudentially optimistic | 0.066*** | 0.057*** | 0.052*** |
| | (0.003) | (0.003) | (0.003) |
| Demographic control variables | No | Yes | Yes |
| Macroeconomic variables | No | Yes | Yes |
| Lagged income and income surprise | No | No | Yes |
| N | 32,248 | 32,248 | 32,248 |

**Table 7**: Forecast errors and updating

Panel A and B report the average marginal effects of past forecast errors ($FE1_{it}$ and $FE2_{it}$ repectively) on changes in expectations ($F\_ch_{it}$) from Ordered probit models. Changes in the expectations take on values "1 = towards more pessimistic", "2 = no change", and "3 = towards more optimistic". Standard errors are clustered at the region-year level and reported in parentheses; *** p<0.001, ** p<0.01, * p<0.05. The data are from the Statistics Finland's Income Distribution Statistics (1994–2009).

| Panel A: FE1 and change in expectation | | | |
|---|---|---|---|
| Ordered probit average marginal effects | Model 1 | Model 2 | Model 3 |
| | Towards more pessimistic | | |
| Clearly pessimistic | -0.360*** | -0.358*** | -0.359*** |
| | (0.007) | (0.007) | (0.007) |
| Moderately pessimistic | -0.210*** | -0.210*** | -0.210*** |
| | (0.003) | (0.004) | (0.004) |
| Moderately optimistic | 0.174*** | 0.174*** | 0.175*** |
| | (0.004) | (0.004) | (0.004) |
| Clearly optimistic | 0.207*** | 0.209*** | 0.212*** |
| | (0.007) | (0.007) | (0.007) |
| | Towards more optimistic | | |
| Clearly pessimistic | 0.346*** | 0.343*** | 0.344*** |
| | (0.006) | (0.006) | (0.006) |
| Moderately pessimistic | 0.201*** | 0.201*** | 0.202*** |
| | (0.003) | (0.003) | (0.003) |
| Moderately optimistic | -0.166*** | -0.167*** | -0.168*** |
| | (0.004) | (0.004) | (0.004) |
| Clearly optimistic | -0.198*** | -0.200*** | -0.203*** |
| | (0.007) | (0.007) | (0.007) |
| Demographic control variables | No | Yes | Yes |
| Macroeconomic variables | No | Yes | Yes |
| Lagged income and income surprise | No | No | Yes |
| N | 66,607 | 66,607 | 66,607 |
| Panel B: FE2 and change in expectation | | | |
| Ordered probit average marginal effects | Model 1 | Model 2 | Model 3 |
| | Towards more pessimistic | | |
| Pessimistic forecast error | -0.222*** | -0.220*** | -0.220*** |
| | (0.003) | (0.003) | (0.003) |
| Prudentially optimistic forecast error | 0.332*** | 0.334*** | 0.334*** |
| | (0.004) | (0.004) | (0.004) |
| Non-prudentially optimistic forecast error | 0.056*** | 0.059*** | 0.060*** |
| | (0.004) | (0.004) | (0.004) |
| | Towards more optimistic | | |
| Pessimistic forecast error | 0.232*** | 0.230*** | 0.230*** |
| | (0.003) | (0.003) | (0.003) |
| Prudentially optimistic forecast error | -0.347*** | -0.348*** | -0.348*** |
| | (0.005) | (0.005) | (0.005) |
| Non-prudentially optimistic forecast error | -0.059*** | -0.061*** | -0.063*** |
| | (0.004) | (0.004) | (0.004) |
| Demographic control variables | No | Yes | Yes |
| Macroeconomic variables | No | Yes | Yes |
| Lagged income and income surprise | No | No | Yes |
| N | 66,607 | 66,607 | 66,607 |

**Table A1**: Descriptive statistics

Panel A reports descriptive statistics on debt-related micro-level variables. Panel B reports the same statistics on continuous and indicator micro-level variables. Panel C reports the proportion of households that belongs to each category of control variables. The data of panels A, B and C are from the Statistics Finland's Income Distribution Statistics (service data 1994–2009). Panel D reports descriptive statistics on macro-level variables from Reuters, Statistics Finland, NASDAQ OMX and the Federation of Finnish Financial Services, including the authors' own calculations.

| Panel A: Debt-related micro variables | | | | | |
|---|---|---|---|---|---|
| | Mean | Median | St. dev. | Min | Max |
| Change in debt (EUR thousand) | 1.274 | 0.000 | 19.078 | -115.000 | 184.993 |
| Debt-to-income ratio | 1.072 | 0.703 | 1.081 | 0.000 | 7.303 |
| Mortgage service-to-income ratio | 0.146 | 0.135 | 0.089 | 0.000 | 0.773 |
| Perceived overindebtedness (dummy) | 0.042 | 0.000 | 0.200 | 0.000 | 1.000 |

| Panel B: Continuous and indicator control micro variables | | | | | |
|---|---|---|---|---|---|
| | Mean | Median | St. dev. | Min | Max |
| Age | 48.708 | 48.000 | 15.079 | 16.000 | 100.000 |
| Gender (1 = male) | 0.662 | 1.000 | 0.473 | 0.000 | 1.000 |
| Retired within a year (dummy) | 0.023 | 0.000 | 0.149 | 0.000 | 1.000 |
| Average income (EUR thousand) | 37.633 | 32.669 | 33.002 | 0.007 | 2866.590 |

| Panel C: Categorical control variables (proportion of households in each category) | | | |
|---|---|---|---|
| **Stage in life** | | **Level of education** | |
| Single | 0.204 | None or unknown | 0.289 |
| Single parent | 0.059 | Secondary-level | 0.409 |
| Couple without children | 0.316 | Lower-degree tertiary | 0.197 |
| Couple with children | 0.395 | Higher-degree tertiary | 0.093 |
| Other | 0.026 | Doctorate | 0.012 |
| **Married** | | **Socioeconomic status** | |
| Single or unknown | 0.251 | Agricultural employer or entrepreneur | 0.073 |
| Married | 0.594 | Other employer and entrepreneur | 0.106 |
| Divorced | 0.102 | Upper-level white-collar employee | 0.187 |
| Widow | 0.054 | Lower-level white-collar employee | 0.162 |
| **Number of children** | | Blue-collar employee | 0.184 |
| No children | 0.634 | Student | 0.027 |
| One or two children | 0.292 | Pensioner | 0.206 |
| More than two children | 0.074 | Long-term unemployed | 0.044 |
| **Age cohort by year of birth** | | Other | 0.010 |
| $<$ 1924 | 0.034 | **Region of residence** | |
| 1924–1926 | 0.017 | Uusimaa | 0.228 |
| 1927–1929 | 0.021 | Varsinais-Suomi | 0.086 |
| 1930–1932 | 0.026 | Satakunta | 0.051 |
| 1933–1935 | 0.029 | Kanta-Häme | 0.032 |
| 1936–1938 | 0.037 | Pirkanmaa | 0.090 |
| 1939–1941 | 0.047 | Päijät-Häme | 0.035 |
| 1942–1944 | 0.051 | Kymenlaakso | 0.035 |
| 1945–1947 | 0.077 | South Karelia | 0.027 |
| 1948–1950 | 0.082 | Etelä-Savo | 0.036 |
| 1951–1953 | 0.078 | Pohjois-Savo | 0.054 |
| 1954–1956 | 0.074 | North Karelia | 0.038 |
| 1957–1959 | 0.070 | Central Finland | 0.056 |
| 1960–1962 | 0.066 | South Ostrobothnia | 0.043 |
| 1963–1965 | 0.064 | Ostrobothnia | 0.033 |
| 1966–1968 | 0.055 | Central Ostrobothnia | 0.014 |
| 1969–1971 | 0.044 | North Ostrobothnia | 0.067 |
| 1972–1974 | 0.036 | Kainuu | 0.019 |
| 1975–1977 | 0.032 | Lapland | 0.035 |
| 1978–1981 | 0.023 | East Uusimaa | 0.014 |
| $>$ 1981 | 0.036 | Åland | 0.006 |

| Panel D: Macro variables | | | | | |
|---|---|---|---|---|---|
| | Mean | Median | St. dev. | Min | Max |
| Short-term interest rate | 0.036 | 0.037 | 0.012 | 0.016 | 0.063 |
| Volatility of short-term interest rate | 0.165 | 0.135 | 0.146 | 0.012 | 0.602 |
| Unemployment rate | 0.097 | 0.091 | 0.025 | 0.064 | 0.154 |
| Real GDP growth | 0.031 | 0.035 | 0.036 | -0.073 | 0.077 |
| Real house price change | 0.037 | 0.038 | 0.051 | -0.075 | 0.206 |
| Real share price change | 0.118 | 0.073 | 0.374 | -0.452 | 0.874 |
| Volatility of share prices | 0.493 | 0.154 | 0.588 | 0.016 | 1.810 |
| Maturity of new housing loans | 14.344 | 13.857 | 2.839 | 11.000 | 19.000 |

**BANK OF FINLAND RESEARCH**
**DISCUSSION PAPERS**

ISSN 1456-6184, online

1/2012 Maria Teresa Punzi **Housing market and current account imbalances in the international economy.** 2012. 27 p. ISBN 978-952-462-784-9, online.

2/2012 Luisa Lambertini – Caterina Mendicino – Maria Teresa Punzi **Expectations-driven cycles in the housing market.** 2012. 61 p. ISBN 978-952-462-785-6, online.

3/2012 George A. Waters **Quantity rationing of credit.** 2012. 26 p. ISBN 978-952-462-786-3, online.

4/2012 Karlo Kauko **Why is equity capital expensive for opaque banks?** 2012. 26 p. ISBN 978-952-462-787-0, online.

5/2012 Kaushik Mitra – George W. Evans – Seppo Honkapohja **Fiscal policy and learning.** 2012. 32 p. ISBN 978-952-462-788-7, online.

6/2012 Ian W. Marsh – Wolf Wagner **Why is price discovery in credit default swap markets news-specific?** 2012. 41 p. ISBN 978-952-462-789-4, online.

7/2012 Katja Taipalus **Signaling asset price bubbles with time-series methods.** 2012. 47 p. ISBN 978-952-462-790-0, online.

8/2012 Paavo Miettinen **Information acquisition during a Dutch auction.** 2012. 22 p. ISBN 978-952-462-791-7, online.

9/2012 Diego Moreno – Tuomas Takalo **Optimal bank transparency.** 2012. 33 p. ISBN 978-952-462-792-4, online.

10/2012 Alina Barnett – Martin Ellison **Learning by disinflating.** 2012. 20 p. ISBN 978-952-462-795-5, online.

11/2012 Bill Francis – Iftekhar Hasan – Qiang Wu **Do corporate boards affect firm performance? New evidence from the financial crisis?** 2012. 55 p. ISBN 978-952-462-796-2, online.

12/2012 Bill Francis – Iftekhar Hasan – Liang Song **Are firm- and country-specific governance substitutes? Evidence from financial contracts in emerging markets.** 2012. 55 p. ISBN 978-952-462-797-9, online.

13/2012 Chung-Hua Shen – Yu-Li Huang – Iftekhar Hasan **Asymmetric benchmarking in bank credit rating.** 2012. 40 p. ISBN 978-952-462-798-6, online.

14/2012 Bill Francis – Iftekhar Hasan – Qiang Wu **Corporate governance and cost of bank loan.** 2012. 49 p. ISBN 978-952-462-799-3, online.

15/2012 Isabelle Distinguin – Iftekhar Hasan – Amine Tarazi **Predicting rating changes for banks: How accurate are accounting and stock market indicators?** 2012. 34 p. ISBN 978-952-462-800-6, online.

16/2012 Bill Francis – Iftekhar Hasan – Liang Song – Bernard Yeung **What determines bank stock price synchronicity? Global evidence.** 2012. 46 p. ISBN 978-952-462-803-7, online.

17/2012 Bill Francis – Iftekhar Hasan – Kose John – Maya Waisman **Urban agglomeration and CEO compensation.** 2012. 64 p. ISBN 978-952-462-804-4, online.

18/2012 Manthos D. Delis – Iftekhar Hasan – Pantelis Kazakis **Bank regulations and income inequality: Empirical evidence.** 2012. 45 p. ISBN 978-952-462-805-1, online.

19/2012 Iftekhar Hasan – Tania De Renzis – Heiko Schmiedel **Retail payments and economic growth.** 2012. 37 p. ISBN 978-952-462-806-8, online.

20/2012 Ari Hyytinen – Jukka Lahtonen – Mika Pajarinen **Entrepreneurial optimism and survival.** 2012. 49 p. ISBN 978-952-462-807-5, online.

21/2012 Ari Hyytinen – Hanna Putkuri **Household optimism and borrowing.** 2012. 45 p. ISBN 978-952-462-808-2, online.

http://www.suomenpankki.fi/en • email: Research@bof.fi
ISBN 978-952-462-808-2, ISSN 1456-6184, online