Cognitive Biases and Consumer Confidence*

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Abstract

We investigate how two cognitive biases affect consumer sentiment. When consumers are systemically affected by cognitive biases, indexes of consumer sentiment can complement objectively defined macroeconomic variables, because they cannot be reduced to averages of either macroeconomic or financial state variables. We show that the peak-end rule and herding influence the index of consumer sentiment published by the University of Michigan. Both biases affect respondents' assessment of changes in their financial position over the past year. First, assessments are more strongly related to extreme detrimental monthly changes during the year than to changes over the whole year, which corresponds with the peak part of the peak-end rule. We rule out that these extremes proxy for risk. Second, the assessments of the past year are positively related to other respondents' expected changes for the coming year on top of their assessment of the past year, which corresponds with irrational herding. Because of these biases, indexes of consumer sentiment are relevant for understanding consumer behavior and for macroeconomic and financial forecasting. They explain why consumer sentiment is more volatile than other macro variables and why it is susceptible to feedback loops.

Keywords: Consumer confidence, cognitive biases, peak-end rule, herding

JEL classification: E71, E32, G41

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1 Introduction

This paper investigates how cognitive biases affect consumer sentiment. Cognitive biases are judgments that cannot be reduced to averages of macro-economic or financial information. They are based on the consumers perception of the past or the future. We use indexes of consumer sentiment to study the possible presence of biases, in this case the Index of Consumer Sentiment published by the University of Michigan. These indexes reflect consumers' opinion of the state of the economy, and are widely regarded as important economic indicators. For example, the Conference Board uses its own sentiment index as a leading economic indicator. We wonder whether systemic cognitive biases can be found in indexes of consumer confidence.

If indexes of consumer sentiment are influenced by cognitive biases, they can complement the information held by other macroeconomic variables by capturing consumers' behavioral deviations from rationality. It has been debated whether they simply constitute an aggregation of fundamental, objectively defined macroeconomic variables, like the growth of industrial production, inflation and the unemployment rate. Van Raaij and Gianotten (1990); Ludvigson (2004) argue that they are economic indicators next to fundamental macro-economic variables. Others state that consumer confidence is simply based on fundamental macro-economic variables, and merely reflects the outlook of the economy without added value in itself (see Carroll et al., 1994, and references therein).

Additionally, it has been questioned whether consumer sentiment actually influences economic activity or only its assessment. A stream of studies underlines the point of view that consumer confidence changes economic activity (Fuhrer, 1988; Carroll et al., 1994; Bram and Ludvigson, 1998; Souleles, 2004), in particular consumer spending, (Acemoglu and Scott, 1994; Carroll et al., 1994; Bram and Ludvigson, 1998; Ludvigson, 2004). Other studies find that consumer confidence has hardly any or only limited influence. For example, according to Fuhrer (1993) consumer confidence reflects sentiments on current, widely known economic conditions, and is no independent cause of economic fluctuations, nor an accurate forecasting variable. Baker and Wurgler (2006); Lemmon and Portniaguina (2006) show that consumer sentiment is useful for predictions in financial markets. Fisher and Statman (2003); Jansen and Nahuis (2003) show the opposite direction where financial markets predict consumer confidence.

For describing cognitive processes as well as cognitive biases, we use the research program related to "the heuristics that people use and the biases to which they are prone in various tasks of judgment under uncertainty" (Kahneman, 2003, p. 1449). Leading in these heuristics is the interaction, or lack thereof, between what is called system 1 (intuitive judgment) and system 2 (reasoning), which represent two types of cognitive processes. System 1 provides us with spontaneous judgment. Judgments in system 1 are fast, automatic, effortless, associative and often emotionally charged, they are also governed by habit and therefore difficult to modify. System 2 differs from system 1 as operations in it are: slower, serial, effortful, and deliberatively controlled; they are also relatively flexible and potentially rule-governed. Crucial for the operation of system 1 is the ease with which mental concepts come to mind, called accessibility. We want to compare system 1 judgments to system 2 judgments. The system 1 judgments are based on on the spot answers that people provide when they are being interviewed, system 2 judgments are based on macroeconomic and financial analysis.

We base our analysis on the data that is gathered to construct the Index of Consumer Sentiment (ICS) which has been published monthly, since 1978, by the University of Michigan. Since 1991, there is an ongoing monthly announcement of preliminary outcomes. This index has always been based on the weighted average responses to five questions about the changes in the respondents' own financial situation over the recent year and their expected changes for the coming year, as well as their judgment of the current economic situation and its outlook for one and five years ahead. These judgments need to take place on the spot, in a telephonic interview, and therefore we consider these to be the system 1 judgments.

We investigate two cognitive biases. Our first question focuses on the influence of the peak-end rule of Varey and Kahneman (1992); Fredrickson and Kahneman (1993); Kahneman et al. (1993) upon the aggregate assessment of past changes in financial positions. Without any biases, the aggregate change should be explained by the yearly returns on the stock and bond markets, the inflation over the past year, and the yearly changes in macroeconomic variables plus perhaps a second order term to account for risk aversion. These are system 2 judgements. The peak-end rule, which belongs to system 1, states that when consumers have to determine changes over a longer period of time, for example a year, they focus on the extremes during shorter periods within that time span, for example, a particular month (peak). They also pay more attention to the most recent change (end).

We compare the explanatory power of the yearly changes in several macro and financial variables to transformations of their monthly changes based on the peak-end rule. We also include the past volatility in our analysis to account for risk aversion. Our results show that past detrimental extremes are better able to explain consumers' assessment of past changes in financial positions but rule out that the proxy for risk. These effects not only apply to broad stock market indexes like the S&P500 and NASDAQ, but also to macro variables such as the growth rate of GNP and the unemployment rate. We do not find evidence for the end-part of the peak-end rule.

These results indicate that the peak part of the peak-end rule is present in the macro setting of consumer sentiment. So far, evidence for the peak-end rule in economics pertains to microeconomic settings of assessing advertisements (Baumgartner et al., 1997) and payments streams (Langer et al., 2005). Nasiry and Popescu (2011) argue that consumers use it when setting reference prices. Psychological evidence for the peak-end role is vast (see surveys by Fredrickson, 2000; Kahneman, 2000). Consistent with this evidence (see Ariely and Carmon, 2000; Aldrovandi and Heussen, 2011), our evidence is strongest for detrimental peaks, such as large losses in financial markets or rises in the unemployment rate.

The second question concerns the sensitivity to herding, i.e. consumers that are overly influenced by the optimism or pessimism of other respondents. We deviate from the common perspective in economics in which herding is mostly related to inference based on the actions of agents or resulting price information (see, for example, the classical model in Banerjee, 1992 or the more general discussion in Chamley, 2004). We investigate how beliefs from earlier respondents influence subsequent respondents' beliefs. Baddeley et al. (2004) use the term herding in relation to forming beliefs. Herding will be rational if an individual has reason to believe that other agents' judgments are based upon better information than their own: other people's judgments become a data-set in themselves. In this way, people will incorporate others' opinions into their prior information set and their posterior judgments may exhibit herding tendencies. However, if agents do not correctly update their judgments, a cognitive bias may arise.

We base this part of the analysis on the influence that the preliminary ICS values have on the ICS values obtained after their announcement. When respondents assess the past changes in their financial positions without any bias, its preliminary aggregate value should perfectly predict its post-announcement value (system 2 judgment). However, there are cognitive biases when the post-announcement value can be explained by the preliminary value for the expected changes for the coming year (system 1 assessment). For example, when optimism of respondents that are interviewed during the first part of the month affects the respondents in the second part. We provide evidence for exactly that effect. The expectations for changes in consumers' future financial position but also for the economy in general that constitute the preliminary ICS values are significantly related to the assessment of past changes in the financial position given by consumers after publication of these preliminary value. Moreover, these effects become larger when we account for systematic differences in the sample composition between the first and second part of the month. We then show how the spread of optimism or pessimism about the future to the assessment of the past creates a feedback loop, as these biased assessment of the past are a source for respondents in the next month to form their assessments and expectations.

Our findings complement the literature on herding and the resulting feedback loops. As it is generally difficult to account for agents' information sets, evidence of herding and feedback loops is to a large extent based on laboratory experiments (see Hommes, 2011, for a survey). He also discusses the evidence on how agents use (past) expectations of others to form their expectations, mostly in relation to prices of financial assets and commodities, or key macro variables such as inflation. In these studies of herding, agents switch between different predictive models. We present evidence that agents do not correctly interpret the information from other agents, using the unique feature of the Michigan survey that it asks respondents to assess past changes in their financial position.

We conclude that indexes of consumer sentiment add information related to behavioral deviations from rationality to the information in macroeconomic and financial state variables. Indexes of consumer sentiment capture these behavioral effects, which makes them relevant for understanding aggregate consumer behavior, and macroeconomic and financial forecasting. In particular, these effects explain why consumer sentiment is more volatile than fundamental macroeconomic variables, and why there are positive feedback loops between consumer behavior and their expectations.

2 Theoretical framework

The starting point of our research is the behavioral framework of Kahneman and Tversky. In this section, we take a closer look at this framework, and relate it to cognitive biases that may arise in indexes of consumer confidence. In particular, we explore the relation with the peak-end rule, herding and the resulting feedback loop.

In the framework of Kahneman and Tversky, cognitive biases are thought of and defined as the distinction and interaction between system 1 and system 2. Using the reasoning of system 2 to make assessments requires effort and time, while the intuitive judgements of system 1 come quickly and spontaneously. Therefore, the assessments under system 1 are prone to cognitive biases. Tversky and Kahneman (1974) discuss three types of heuristics that can create these biases: representativeness, availability and anchoring (see also Baddeley et al., 2004). These heuristics enlarge the accessibility, which is crucial for assessment by system 1. Representativeness implies that an agent judges the likelihood of a specific event by how representative the event is of the stereotype of that event. Availability means that people judge the likelihood of a specific event by the ease with which they can come up with an example of the event. Anchoring means that people bias the likelihood of a specific event towards an initial value that may come from the problem statement. These heuristics can be seen as the base for cognitive biases: they link to system 1 and deviate from system 2. Kahneman and Frederick (2002) elaborate on this work. They do not adhere to the three types but look for a more general mechanism. According to them the reduction of complex tasks to simpler operations is achieved by an operation of attribute substitution (Kahneman, 2003, p. 1460): "Judgement is said to be mediated by a heuristic when the individual assesses a specified target attribute of a judgement object by substituting another property of that object – the heuristic attribute – which comes readily to mind."

We wonder where heuristics may occur in the construction of the Michigan Index of Consumer Sentiment (ICS). We therefore turn to the interviews in which the judgements are expressed. The composition of the ICS is based on questions that are part of the Michigan Survey of Consumer Attitudes and Behavior (CAB). We introduce these questions first, and then discuss how cognitive biases may be present. The CAB lets respondents choose from a number of answer categories, that are given an ordinal integer value from 1 to 5, with a lower value indicating a better assessment. Respondents can also answer "don't know". The questions and corresponding answer category labels are as follows. We indicate in parenthesis how we will refer to the question.

- We are interested in how people are getting along financially these days. Would you say that you are better off or worse off financially than you were a year ago? (abbreviation PAGO, from Personal finances compared to a year AGO.)

  Category labels: Better now (1), Same (3), Worse now (5).

- Now looking ahead–do you think that a year from now you will be better off financially, or worse off, or just about the same as now? (abbreviation PEXP, from Personal finances EXPected a year from now.)

Category labels: Better now (1), Same (3), Worse now (5).

- Now turning to business conditions in the country as a whole–do you think that during the next 12 months we'll have good times financially, or bad times, or what? (abbreviation BUS1Y, from BUSiness Conditions 1 Year ahead.)

  Category labels: Good times (1), Good with qualifications (2), Pro-con (3), Bad with qualifications (4), Bad times (5).

- Looking ahead, which would you say is more likely – that in the country as a whole we'll have continuous good times during the next 5 years or so, or that we will have periods of widespread unemployment or depression, or what? (abbreviation BUS5Y from BUSiness conditions 5 Years ahead.)

  Category labels: Good times (1), Good with qualifications (2), Pro-con (3), Bad with qualifications (4), Bad times (5).

- Generally speaking, do you think now is a good or a bad time for people to buy major household items? (abbreviation DUR from DURables)

  Category labels: Good (1), Pro-con (3), Bad (5).

Answering the questions takes place in telephone interviews, which invites a quick assessment as interviewees have to answer on the spot. Therefore we assume that these judgements take place under system 1, and that heuristics are used to answer the question. Under system 2 respondents would incorporate all different variables in a balanced way, both with regard to their personal financial position and the economic situation in general.

The first heuristic we consider is the peak-end rule. The peak-end rule of Fredrickson and Kahneman (1993) states that agents replace a sum (or average) of a series of hedonic experiences by the most extreme and the final experience. In our setting, it means that agents look at the largest increases or decreases in financial and macro variables and the most recent changes (system 1 judgements), instead of the yearly changes (system 2 judgements). If assessment by system 1 has a large effect on PAGO, we should find that the explanatory power of extremes and recent changes exceeds that of yearly averages. So, in the first part of the research we question whether peak and end experiences are dominant in the final assessment. Unfortunately, we cannot make a comparable reconstruction for the present (DUR) and the future (PEXP, BUS1Y and BUS5Y). In order to find out whether the peak-end rule is at stake, past experiences are required.

Second we concentrate on herding. Under system 2, rational herding can occur, which Bikhchandani and Sharma (2000) split in spurious and intentional herding. The first occurs, if all agents update their beliefs in the same way because of the arrival of new information. The second can occur for several reasons: agents may copy others who have better information sets or processing capabilities; they may want to enhance or protect their reputation by following the crowd; or they may want to be part of a group.[1] Herding can also be irrational, which occurs when agents deviate from correct Bayesian learning and put too much weight on other's information. This form of herding can be interpreted as a cognitive bias, as judgements in system 1 deviate from system 2 judgements. Tversky and Kahneman (1974) relate this deviation to anchoring.

To investigate the presence of herding it is important to take a closer look at how the interviews are set up. The interviews take place in two rounds. Based upon a first, and smaller round of interviews, preliminary results are gathered and published. After a second round of interviews, final results are published. Based on the data set of the Michigan Survey, the results based on the interviews after the announcement can be constructed. Generally, relations between the preliminary and post-announcement values can be signs of herding, either rational or irrational. So, there can be a rational relation between e.g. PAGO prelim and PAGO post announcement. In system 2, agents should answer the PAGO question by considering the difference in their financial position currently and a year ago. The differences can be approximated by the past yearly changes in indexes for financial markets (stocks and bonds) and the housing market, changes in interest rates and in price indexes, and more generally changes in the economic environment. They can also use the assessment of others about their changes in their financial position, to the extent that these other agents are in comparable situations. However, a relation from the prelim values of one of the forward-looking variables (PEXP, BUS1Y and BUS5Y) to the the post-announcement backward-looking variable (PAGO) points at irrational herding. The assessment of the future by one group of agents should not have an effect on another group's assessment of the past. Finding such an effect is again evidence of assessment under system 1. It means that agents use preliminary future oriented results (PEXP) as heuristics for post-announcement PAGO.

[1] These motives for herding go back to Keynes (1930). See also Baddeley (2010) for a discussion.

The presence of irrational herding can lead to feedback loops. Shocks in the prelim values of PEX, BUS1Y and BUS5Y, can spill over to the post-announcement and hence the final value for PAGO. If respondents in the next round use the final value of PAGO as an anchor to give their answers to the Michigan Survey, the shocks will further propagate in the system. Further, this effect will repeat itself in the next months.[2] Consequently, we should see larger swings in the ICS and higher volatility than what we can explain by objectively measured economic variables.

3 Data

3.1 Consumer Sentiment Data

The Michigan survey determines the aggregate answer to each question in the previous section by subtracting the percentage giving unfavorable replies (i.e. answers with a higher label than the middle label) from the percentage of respondents giving favorable replies (i.e. answers with a lower label than the middle label), and rounding to the nearest whole number. Both percentages are taken with respect to the total number of respondents, so including "don't know", and are weighted to yield a representative sample of all U.S. Households.[3] They add 100, which means that each aggregate answer lies in the range $[0, 200]$. A value of 0 (200) means all respondents are negative (positive), whereas a value of 100 means that positive and negative responses are balanced. This "diffusion index" is then scaled with respect to a base period (see Ludvigson, 2004, p. 35, for an example).

This procedure can be interpreted as an ordered choice model. To easily link our analyses to the construction of the variables, we briefly discuss this model for PAGO. We assume that each respondent i determines the change in her financial position. We label this variables $PAGO^*_{it}$. She use thresholds to transform it to the ordered categorical variable

$$PAGO_{it} = \begin{cases} 1 & \text{if } \; PAGO^*_{it} \geq \gamma_{i,2} \\ 3 & \text{if } \; \gamma_{i,1} \leq PAGO^*_{it} < \gamma_{i,2} \\ 5 & \text{if } \; PAGO^*_{it} < \gamma_{i,1}, \end{cases} \tag{1}$$

with $\gamma_{i,1} < \gamma_{i,2}$. The aggregate $PAGO_t$ is calculated as a weighted average of $PAGO_{it}$,

[2] By construction, the ICS and the constituting variables are bounded, which means that the effect of a shock has to die out eventually.

[3] See `https://data.sca.isr.umich.edu/fetchdoc.php?docid=24773` for more information.

centered such that if all respondents report $PAGO_{it} = 3$ the result is 100,

$$
\begin{aligned}
PAGO_t &= 100 \sum_{i=1}^{n} w_i \big(1 + I(PAGO_{it} = 1) - I(PAGO_{it} = 5)\big) \\
&= 100 \sum_{i=1}^{n} w_i \big(I(PAGO^*_{it} \geq \gamma_{i,1}) + I(PAGO^*_{it} \geq \gamma_{i,2})\big),
\end{aligned}
\tag{2}
$$

where w_i measures the weight of respondent i, $\sum_{i=1}^{n} w_i = 1$, and I is the indicator function, that returns one if the argument is true. For PEXP and DUR, the same model applies. For BUS1Y and BUS5Y five answer categories exist, but answers labels 1 and 2, and 4 and 5 are treated as one category when $BUS1Y_t$ and $BUS1Y5Y_t$ are determined.

Next, the value of the ICS at time t is computed as

$$
ICS_t = \frac{PAGO_t + PEXP_t + BUS1Y_t + BUS1Y5Y_t + DUR_t}{6.7558} + 2.0, \tag{3}
$$

where the sum of the five aggregate answers is divided by the 1966 base period total of 6.7558 and the added 2.0 is a constant to correct for sample design changes from the 1950s.[4] The value of ICS_t as well as the constituting aggregate sentiment variables is published every month.

Table 1 gives summary statistics of the ICS and the constituting variables over the full sample period from January 1978 until December 2014. Because ICS has a different scale, its numbers are typically lower than for the constituting series. When the weighted fractions of favorable and unfavorable replies are equal, the ICS takes a value of 76.0. Consequently, respondents are on average mildly positive. Respondents were most negative in May 1980, (ICS: 51.7) and most positive in January 2000 (ICS: 112).

[Table 1 about here.]

As a value above 100 for the constituting series indicates that more respondents are positive than negative, we on average observe optimism for all questions, except for business conditions on the long term (BUS5Y). Respondents are most positive about DUR, followed by PEXP, PAGO and BUS1Y. Minima and maxima typically occur with a difference of only a few months, though the actual values can differ quite a bit. This is also reflected in the different standard deviations of the series. The correlations of the constituting variables in

[4] There was no constant added until 1972:4 (except for 1972:1), from 19724 until 1981:11 the constant was 2.7, and from 1981:12 to present the constant is 2.0.

panel (b) between 0.70 and 0.88 mean that they are closely related but not copies of each other.

To check whether the series are stationary, we analyze the time-series properties in Appendix A. The results for the ICS, BUS1Y, BUS5Y and DUR series clearly indicate stationarity. The stationarity tests for PAGO and PEXP leave some room for a unit root process. Further analyses show the presence of both AR and MA effects of order 1 or 2. We typically observe that shocks die out slowly, which is related to the overlapping windows to which the questions refer. We consider all series as stationary, and adjust our tests for the strong autocorrelation structure.

4 PAGO and the Peak-End Rule

In this part of our research, we investigate whether respondents are susceptible to the peak-end rule of system 1 when they determine $PAGO_{it}$. If this bias is systematic, it will also influence the aggregate value of $PAGO_t$.

4.1 Methodology

Let y_{it} be the financial position of respondent i at time t, with t in months. PAGO asks for the change in the financial position over the past year, so the change between y_{it} and $y_{i,t-12}$. To answer this question, the respondent can calculate the values for her financial position for both points in time, or she can aggregate the changes over each period in time, as $y_{it} - y_{i,t-12} = \sum_{s=0}^{11} \Delta y_{t-s}$, with the operator Δ giving the one-period change in a variable, $\Delta y_t = y_t - y_{t-1}$. Because a complete calculation of the financial position requires precise and possibly extensive information of an agent's assets, aggregating a small set of changes may be easier. In particular, she can use the relation with state variables and aggregate their changes. In this approach, the change in the financial position is split in a part that can be explained by a set of state variables $x_{j,t}$, $j = 1, \dots, m$, and a part unrelated to this set,

$$\Delta y_{it} = \sum_{j=1}^{m} \beta_{i,j} x_{j,t} + \eta_{it} \tag{4}$$

where $\beta_{i,j}$ is the sensitivity of the respondent's financial position to variable j, and η_{it} captures the unexplained part. State variables that are relevant for the value of assets are the changes in stock, bond and house price indexes, whereas changes in price and production indexes or in the unemployment rate are relevant for income and income uncertainty.[5]

Under system 2 both ways of answering this question yield the same answer. However, when agents use system 1, the answers can differ, because agents show biases when they aggregate. In particular, they use the peak-end rule as termed by Fredrickson and Kahneman (1993). They make a heuristic assessment under system 1, where they use the most recent and the most extreme change to represent the yearly change.

To investigate how the peak-end rules influences $PAGO_{it}$, we define different rules, being the rational, peak, bottom and end rules, and gather them in a set $\mathcal{R}$. Each rule r is as a function g^r that operates on a sequence of n past observations $\boldsymbol{z}_t^n = (z_{t-n+1}, \ldots, z_t)'$ (cf. Cojuharenco and Ryvkin, 2008). We take the variables z_t as flow variables. The function for the rational rule $r = \mathrm{ra}$ equals

$$g^{\mathrm{ra}}(\boldsymbol{z}_t^n) = \sum_{s=1}^{n} z_{t-n+s}. \tag{5}$$

A respondent who uses the rational rule correctly aggregates the flow variables by summing them.

When a respondent uses a peak or bottom rule, she pays attention to the largest or smallest realization over a single period or over multiple subsequent periods

$$g^r(\boldsymbol{z}_t^n) = \begin{cases} \max\{z_{t-n+1}, \ldots, z_t\} & \text{for } r = \mathrm{sp} \\ \max\{\sum_{s=p}^{q} z_{t-n+s}; p, q = 1, \ldots, n, p < q\} & \text{for } r = \mathrm{mp} \\ \min\{z_{t-n+1}, \ldots, z_t\} & \text{for } r = \mathrm{sb} \\ \min\{\sum_{s=p}^{q} z_{t-n+s}; p, q = 1, \ldots, n, p < q\} & \text{for } r = \mathrm{mb}. \end{cases} \tag{6}$$

In the abbreviation of the rules, s stands for single, m for multiple, p for peak and b for bottom. We investigate both peaks and bottoms, because the variables need not have an upper or lower bound. The peak rule originates from variables with a lower bound, which makes only the peak relevant.[6] We also allow for the largest cumulative increase or decrease, as they produce the peaks and bottoms in the aggregated series. We use the term extreme-rules to jointly refer to these four rules.

[5]The Michigan survey asks for a reason which can pertain to income, prices, the value of assets, and the value of debt, see `https://data.sca.isr.umich.edu/sda-public/sca/Doc/sca.htm`.

[6]Varey and Kahneman (1992) investigate the assessment of unpleasant experiences, Fredrickson and Kahneman (1993) the assessment of pleasant or aversive film clips, and Kahneman et al. (1993) the assessment of a painful episodes.

The end rule only pays attention to the most recent realization in a sequence,

$$g^{\mathrm{se}}(\boldsymbol{z}_t^n) = z_t \tag{7}$$

The respondent can use these rules to answer the PAGO question, which means

$$PAGO_{it}^* = \sum_{r\in\mathcal{R}} \sum_{j=1}^{m} \beta_{i,j}^r g^r(\boldsymbol{x}_{j,t}^n) + \sum_{r\in\mathcal{R}} \beta_{i,0}^r g^r(\boldsymbol{\eta}_{it}^n) \tag{8}$$

is used in Equation (1). The coefficients $\beta_{i,j}^r$ reflect how strong a particular rule influences the aggregation of a particular variable. When $\beta_{i,j}^r \neq 0$ for rule r and zero for all others, the respondent only uses that particular rule in the aggregation. When $\beta_{i,j}^r \neq 0$ for several rules r, the respondent combines them when determining $PAGO_{it}^*$. When $\beta_{i,j}^r = \beta_{i,j}$ for $r = \mathrm{ra}$ and zero for all others for $j = 0, 1, \ldots, m$, the agent is fully rational, and Equation (8) reduces to

$$PAGO_{it}^{\mathrm{ra}} = \sum_{j=1}^{m} \beta_{i,j} \sum_{s=1}^{n} x_{t-n+s} + \sum_{s=1}^{n} \eta_{i,t-n+s}. \tag{9}$$

The rules that the respondents use to determine $PAGO_{it}^*$ influence the aggregate $PAGO_t$. Substitution of Equation (8) in Equation (2) yields

$$\begin{aligned} PAGO_t = 100 \sum_{i=1}^{n} w_i \Bigg(I \Bigg(\sum_{j=1}^{m} \sum_{r\in\mathcal{R}} \beta_{i,j}^r g^r(\boldsymbol{x}_{j,t}^n) + \sum_{r\in\mathcal{R}} \beta_{i,0}^r g^r(\boldsymbol{\eta}_{it}^n) \geq \gamma_{i,1} \Bigg) + \\ I \Bigg(\sum_{j=0}^{m} \sum_{r\in\mathcal{R}} \beta_{i,j}^r g^r(\boldsymbol{x}_{j,t}^n) + \sum_{r\in\mathcal{R}} \beta_{i,0}^r g^r(\boldsymbol{\eta}_{it}^n) \geq \gamma_{i,2} \Bigg) \Bigg). \end{aligned} \tag{10}$$

Because of the transformation to categorical variables and the respondent-specific thresholds, the relation between $PAGO_t$ and the state variables $x_{j,t}$ is a step function. When the number of respondents n becomes larger, the steps become smaller. We use a linear approximation to investigate the effects of the different rules,

$$PAGO_t = \alpha + \sum_{j=1}^{m} \sum_{r\in\mathcal{R}} \beta_j^r g^r(x_{j,t-n}, \ldots, x_{j,t}) + \varepsilon_t, \tag{11}$$

where α is a constant and ε_t contains the approximation error. Because the idiosyncratic parts η_{it} are unobservable, we include their effect in α and ε_t. We can determine the importance of a rule r by applying it to a state variable x_{jt}, and then estimate the coefficient β_j^r

by a linear regression.

4.2 Empirical design

The set of financial state variables that we use consists of the returns on the stock market, proxied by the S&P500 and returns on the bond market, proxied by the Barclays Aggregate Bond Index. Since housing wealth can make up a substantial position of the total wealth of consumers, we include the All Transactions House Price Index compiled by the US Federal Housing Finance Agency. This index has a quarterly frequency. We also include changes in the 3-month T-Bill rate and 10-year government bond rate.

In the set of macro variables we include the growth rates of the consumer price index (CPI), GNP, total nonfarm payrolls (NFP), and personal consumption expenditures (PCE), as well as the change in the unemployment rate. All variables are available at a monthly frequency, except GNP which has a quarterly frequency. Because macro variables are typically published with a lag, we use vintage data made available by the Federal Reserve Bank of St. Louis. We assume that respondents always use the first vintage. We assume that the financial variables do not have a publication lag. More information about the variables is in Appendix A.

To investigate the influence of the different rules, we construct yearly aggregates based on the transformations in Equations (5) to (7). For the monthly (quarterly) series, we always use the twelve (four) most recent observations before the start of a month to construct the yearly aggregates. In total, we construct six series for each variable, the actual yearly change based on the rational rule, four extreme-rule series, and one end-rule series. The first rule corresponds with system 2, the other five with system 1 judgements.

We report summary statistics of these series in Table 2. The average yearly changes in the stock market and the bond market are positive. However, monthly fluctuations can be large. The averages for the single-peak and single-bottom transformations are sizeable, so the yearly aggregation can differ substantially from the largest and smallest return during the year. The low correlations of sp and sb with ra in panel (b) also point in this direction. Very good and very bad months do not happen in isolation but form streaks as indicated by averages for the mp and mb series that are (in modulo) larger. Because they comprise several months, their correlations with the yearly average is automatically larger. The end rule has an automatic overlap of 1 month out of 12 with the yearly average, but gives a reasonable approximation of the whole year as indicated by the correlations of 0.30 and 0.34.

[Table 2 about here.]

Both the short and long-term interest rates have gone down over the sample period on average, with single-period shocks of similar size in both directions. Interest rates can go up and down for a couple of months, as indicated by the average values for mp and mb. The correlation of the mp and mb transformations with the yearly changes lies between 0.49 and 0.72, which shows that these series contain different information than the yearly average.

The housing market also shows steady increases and is less volatile than the stock and bond markets. Consequently, the largest peak is on average more moderate, and the smallest return during the year is on average even positive. All correlations of the peak-end transformations with the yearly changes are high (> 0.85), which points at strong persistence in the quarterly series.

The means and volatilities of the macro variables indicate more gradual increases than for the financial variables, except for the unemployment rate. The growth rates of CPI, GNP, NFP and PCE are all positive, and the averages for the peak series are moderate compared to the yearly average. Their correlations with the yearly average are high. The growth rates of CPI and GNP show right-skewness, because the average of the single-peak series deviates more from the monthly mean than the average of the single-bottom series. This effect caries over to the multi-period series. NFP and PCE are less skewed, though streaks of months with increases last longer than streaks of months with decreases. Correlations of the sp and mp series with the ra series are typically larger than those of the sb and mb series. The high correlations of the end series with the yearly averages point again at strong persistence.

The unemployment series deviates from the other macro variables. Partly this is by construction, as the unemployment rate has a fixed scale and cannot show a pronounced trend. Changes in unemployment are symmetric, as the averages for the peak and bottom series are similar in magnitude. However, the standard deviations show that increases vary more in size than decreases. Correlations for peak series are larger than for bottom series. The large correlation of the end-rule transformation with the the yearly average points again at autocorrelation.

To find whether one of the peak-end rules can better explain PAGO than the rational rule, we regress the PAGO series on the yearly averages and the peak-end series that we have created. If so, the peak-end series should yield a higher R^2 in a single regression. Second, the coefficient on the yearly average should decrease (in modulo) and become less significant when we add the peak-end series to the regression. Because PAGO refers to the yearly change and we use monthly observations, we use HAC standard errors based on Newey and West (1987) with a Bartlett kernel and a bandwidth value of 12.

An important concern for our analysis is the role of risk aversion. Risk-averse respondents prefer smooth over volatile changes. The difference between the extreme and the total change during the year is a proxy for the volatility. A multiple regression of the total change and one of the peak series may hence show the effect of volatility. We account for this possibility in two ways. First, we focus on the signs of the coefficients. If the respondents substitute one of the extreme series for the yearly change, its coefficient should have the same sign. If it proxies for volatility, is should be negative (positive) in case of a peak (bottom) series in a multiple regression with the yearly change. So, when moving from a single to a multiple regression leads to a coefficient that switches to positive for the sp and mp-series or negative for the sb and mb-series, this can be an indication of a volatility effect. Changes in sign may also be caused by the high correlations between the series as in Table 2b, so care is needed. Second, we conduct another regression in which we also include the volatility of the explanatory variable during the year. If the extreme series proxies for volatility, its effect should diminish, because the volatility is a more precise measure for the variation of the series. Because we use the total yearly change instead of the monthly (or quarterly) average, we also annualize the volatility.

4.3 Results

We present the results for the financial variables in Table 3. Panel (a) shows that the return of the S&P500 over the past year has a positive influence on PAGO. A one standard deviation increase in the yearly return leads to an increase of $16.17 \times 0.35 = 5.66$. This effect is significant at the 5% level, and corresponds with an R^2 of 11%. Our results for the four extreme-rules show that the series of the multi-period bottoms has a significant explanatory effect on PAGO that is larger than the effect of the yearly change (R^2 of 15%). In the multiple regression of PAGO on the ra and mb series, the coefficient for the first is insignificant. If we add volatility as a regressor, the coefficient of the mb-series increases, and the volatility coefficient is positive and significant. Although the sign for the volatility coefficient goes against our expectation, these outcomes indicate that the mb-series is not used as a volatility proxy, but replaces the yearly change. Peaks (sp and mp), single bottoms (sb) and the most recent observation do not explain PAGO. We conclude that consumers pay more attention to sequences of losses in the stock market during the year than to the changes over the whole year.

[Table 3 about here.]

[Table 3 (continued) about here.]

Table 3b shows that the yearly return on the bond market, proxied by the Lehman Aggregate Bond Index does not help explaining PAGO, but its volatility does. The single and multi-period peaks and bottoms do have explanatory power, but this seems mostly related to volatility. The effect of the peaks is negative, whereas that of the bottoms is positive, and if volatility is included as a regressor their effect disappears. The end rule has again no explanatory power.

Interest rates may be more salient than the bond market or the index we consider. However, we find that the yearly changes in neither short- nor long-term interest rates offer explanatory power for PAGO (Table 3c and d). Consistent with the result for the bond index, interest rate volatility has a significantly negative effect on PAGO. The effects of peaks and bottoms is again in line with a volatility explanation. In the multiple regression with the yearly change in the 10-year interest rate, its largest decrease and volatility, both the sb and ra-coefficients are significant but have opposite signs. We conclude that changes in neither bond market returns nor interest rates are consequential for PAGO.

Increases in house prices (Table 3e) have a significant positive effect on PAGO with an R^2 of 23%. The volatility is also important, as it increases the R^2 to 58%. Our results for the single and multi-period bottoms are again consistent with the peak-end rule. In the single regressions, the sb- and mb-coefficients have the same sign as ra-coefficient, and their explanatory power at 37 and 43% is larger. If we regress PAGO on the sb and ra-series the ra-coefficient becomes significantly negative. If also the volatility is added, both other coefficient are insignificant. Because the Wald test that the coefficients are jointly zero is mildly rejected with a p-value of 0.134, it seems that the respondents use the sb-series as a partial substitute for the ra-series. The mb-series is used as a full substitute for the ra-series. The mb-coefficient has the correct sign in all three regressions, and is significant at the 1% level if the ra-series is used next to it as a regressor, and 5% level if volatility is added. The ra-coefficients are insignificant in both cases. The single and multi-period peaks in house price changes seem important, but their effect is consistent with a volatility explanation. The end-rule has some explanatory power, but not enough to replace the year change. So, just as for the stock market, sequences of losses in the housing market are more important than yearly changes.

Concluding, our results present evidence that respondents use the peak-rule under system 1 applied to financial state variables to answer the PAGO questions. Both for the S&P500 and the house price index, the explanaotry power of the multi-period bottom series is higher than of the yearly change series. We show in Table A.4 that around 75% of the respondents own their house, and 60% invest in stocks, underlining the relevance of these variables. Wtih regard to information from the bond market index and interest rates, only volatility seems to be important. This makes it impossible to see a replacement by the peak-end rule. We find no evidence of the end-rule.

We report the explanatory power of macro variables for PAGO in Table 4. Inflation reduces the real value of wealth, and consequently the yearly change in CPI has a negative and significant effect on PAGO with an R^2 of 6%. Inflation uncertainty has a strong negative effect on PAGO, as indicated by the large negative coefficient and the increase in R^2. The results for the mp-series point at substitution. In a single regression, its coefficients has the right sign, and its R^2 exceeds that of the regression with the ra-series. In both multiple regressions the mp-coefficients are significant, and the ra-coefficient changes sign. However, it remains significant, which may be caused by the high correlation between the ra- and mp-series. Though increases in the price index over a sequence of months seem to replace the yearly change, the sp, sb and sp series proxy for volatility. The sp-series has a negative effect on PAGO in the single regression, but it disappears if volatility is included. The signs for the sb and mb-coefficients are positive and opposite to the ra-coefficient. The end-rule has no effect on PAGO. So, also multi-period peaks in inflation are better at explaining PAGO than the total yearly inflation.

[Table 4 about here.]

[Table 4 (continued) about here.]

Economic growth, as measured by the change in log GNP has a positive effect on PAGO. Volatility of GNP has a negative effect on PAGO but is not significant. The bottoms in GNP growth are again more informative than the yearly change. The signs of their coefficients are the same as for the ra-series, and the R^2 in single regressions is larger. In multiple regressions, the ra-coefficients lose their significance, and the results do not disappear if volatility is included. The explanatory power of the multi-period bottoms is a bit larger than of single-period ones. The single regressions show that the peaks in GNP growth have less explanatory power than the yearly change, and that they proxy for volatility in the multiple regressions. We find some evidence that the end-rule is combined with the yearly change, as both the ra and end-coefficient are positive, but the hypothesis that they are jointly zero is not rejected.

The change in non-farm payrolls (Table 4c) exhibits strong explanatory power for PAGO with an R^2 of 0.30, which is the largest we find for any ra-series. Here, we do not find evidence for the extreme rules. The peaks have less explanatory power than the yearly change, or proxy for volatility in the multiple regressions. The bottoms have more explanatory power than the peaks, but less than the yearly change. If combined with the ra- and volatility series, the effect of the bottom series disappears. The most recent NFP observation has a significant coefficient, though the single regression R^2 is smaller than in the case of yearly change. If combined with the ra- and volatility series, the end-coefficient is significant at the 5% level.

The yearly change in the unemployment rate and its volatility both have a strong negative effect on PAGO. The multi-period peak turns out to be more informative than the yearly change. Its single regression R^2 is larger (35 compared to 29%), the ra-coefficient becomes insignificant in the multiple regressions, and the effect does not disappear if volatility is included. Single period peaks are less informative than multi-period peaks and yearly changes, and the bottom series proxy for volatility. We do not find evidence for the end-rule.

We end this analysis by looking at changes in personal consumption expenditures. Its yearly changes have explanatory power for PAGO, which is not exceeded by any of the peak-end transformations. However, the results of the multiple regressions with either the sb- or mb-series are consistent with a partial replacement of the ra-series. If the sb-series is included, the coefficients for the ra-series go down, and the sb-coefficients have the same sign though they are insignificant. The mb-coefficients are significant at the 5% level, and if volatility is also included, the ra-coefficient is no longer significant. The end-series does not have explanatory power.

The results for the macro variables are in line with our results for the financial variables. Detrimental extremes, so peaks in inflation and unemployment, and bottoms in growth of GNP and consumer expenditures are better able to explain PAGO than the yearly changes in these variables. We show that their effect cannot be explained by risk aversion. We generally do not find evidence for the end-rule. The only exception is non-farm payrolls, where we do not find evidence for the peak-rule, but some evidence for the end-rule.

4.4 Robustness checks

The interviews take place during the whole month. The past year thus slightly differs for respondents, depending on the day of the month they are interviewed. However, we assume that the information set of each respondent is the same, and contains only information available at the beginning of the month in which they are interviewed. In reality respondents update their information set. While a couple of days or weeks may generally not make much of a difference, a large (negative) surprise in one of the variables will influence the assessment of the respondents that are interviewed after the event. This may mean that our analysis of the end-rule ignores important information. Therefore we conduct a robustness check where we include the information that becomes available during the month.

Our results in Table 5 indicate that respondents are also not systematically influenced by the end-rule if we include contemporaneous information in our analysis. R^2-values are a bit higher than in the previous tables, but do not come close to the values produced by the rational rule.

[Table 5 about here.]

5 Herding

We now turn our attention to herding. As argued in Section 2, under system 2 there should be no effect of the one respondent's future expectations (PEXP, BUS1Y and BUS5Y) in the Michigan survey on the past assessment in PAGO of another respondent, other than what can be explained by the first respondent's past assessment. We interpret the presence of such an effect as evidence of the anchoring heuristic under system 1.

Any analysis of herding outside a laboratory environment is complicated, because the researcher can never completely account for the information set that the respondent uses. A respondent can only include another respondents expectations after they have been formed, which means that part of the expectations can already have been realized. We want to exploit the preliminary announcement of the consumer sentiment variables during the month. By comparing the answers before and after the announcement, the overlap between the past year after the announcement, and the coming year (or five years for BUS5Y) before the announcement is minimal.

5.1 Empirical design

Preliminary values for the ongoing month are generally based on the first 330 out of 500 interviews. These preliminary values are announced on the second or third Friday of the month, based on the interviews until the Wednesday before that Friday. We use the term "final" to refer to the value for each variable based on all interviews for a given month, and "prelim" for the preliminary values. The prelim series are available since January 1991.

Based on this setting, we create two additional series ourselves, being the "post-announcement" (or"pa") series which starts in January 2000, and the "non-prelim" (or "np") series which starts in January 1991. We construct the pa-series based on the interviews that are taken after the announcement of the preliminary values for the sentiment variables. To construct it, we use the fully detailed interview results and their weights that are available from January 2000.

We construct the np-series based on all interviews that are not used for the "prelim" series. It includes the interviews in the post-announcement period and the interviews that are taken after the last interview included in the prelim series, but before the announcement of the preliminary sentiment values. To construct this series we use again the detailed results and weights available as of January 2000. For the period from January 1991 to January 2000 we use the difference between the prelim and final values, using the average weights based on the period after 2000. Consequently, the np-series contains 10 years more of observations, which increases the statistical power of our tests.

We investigate the relation between the post-announcement value of PAGO, $PAGO_t^{\mathrm{pa}}$ and the preliminary values of the forward-looking variables (PEXP, BUS1Y and BUS5Y), collected in a vector $\boldsymbol{x}_t^{\mathrm{prelim}}$, by a linear regression

$$PAGO_t^{\mathrm{pa}} = \alpha + \beta PAGO_t^{\mathrm{prelim}} + \boldsymbol{\gamma}'\boldsymbol{x}_t^{\mathrm{prelim}} + \boldsymbol{\delta}'\boldsymbol{z}_t + \varepsilon_t, \quad \varepsilon_t \sim \mathrm{N}(0, \sigma^2). \tag{12}$$

Because we include $PAGO_t^{\mathrm{prelim}}$ in this regression, $\boldsymbol{\gamma}$ captures the effect that the forward looking variables have after correction for the correlation between them and $PAGO_t^{\mathrm{prelim}}$. We allow for the inclusion of m covariates $\boldsymbol{z}_t$ that account for systematic deviations between the prelim and pa sub samples.

Under system 2, the assessment of the future by the agents in the prelim group should not have an effect on the assessment of the past by the agents in the pa group, other than what can be explained by the prelim group's assessment of the past. This corresponds with the hypothesis $\boldsymbol{\gamma} = \mathbf{0}$, which we test against $\boldsymbol{\gamma} \neq \mathbf{0}$ by t- and F-tests. If $PAGO_t^{\text{prelim}}$ is an unbiased predictor of $PAGO_t^{\text{final}}$, it should also be an unbiased predictor of $PAGO_t^{\text{pa}}$, which implies $\alpha = 0, \beta = 1$ and $\boldsymbol{\gamma} = 0$. We test this hypothesis against the two sided alternative also by an F-test.

The prelim and pa subsamples may exhibit structural differences. The Michigan survey aims at a representative sample over the complete month, so they may target specific groups that are under represented in the first part of the month. From January 2000 onwards, demographic characteristics related to age, family composition, education and financial position are available. For each month, we calculate the weighted average value of a characteristic, or the frequency of a particular answer. We split the observations in those belonging to the prelim-period and to the pa-period. We use the differences, calculated as the pa-values minus the prelim-values as the control variates in Equation (12). We provide details and summary statistics of the demographic variables in Appendix A.3.

5.2 Results

Table 6 presents our results of the regressions of post-announcment values of PAGO on the preliminary values of the different forward-looking variables. Panel (a) shows that the pa respondents' assessments of past changes in their financial position are positively related to the prelim respondents' expectations about changes in their personal financial position over the year to come. For our longest series, the $PAGO_t^{\text{np}}$ series, a one point increase in $PEXP_t^{\text{prelim}}$ leads to an increase of 0.21 in $PAGO_t^{\text{np}}$. This increase is significant at the 5% level. The test that $PAGO_t^{\text{prelim}}$ is an unbiased predictor of $PAGO_t^{\text{np}}$ leads to a Wald statistic of 7.34, with a p-value below 0.1%. Repeating this analysis for the shorter period for which we can precisely construct the pa-series leads to similar results. The coefficient estimate of 0.18 for $PEXP_t^{\text{prelim}}$ is a bit smaller, but still significant at the 10% level, and we still reject $PAGO_t^{\text{prelim}}$ being an unbiased predictor.

[Table 6 about here.]

[Table 6 (continued) about here.]

We show in Appendix A.3 that the pa-respondents differ from the prelim-respondents with respect to most demographic characteristics. These differences may contaminate our regression results. We therefore include the differences between the weighted average values for the prelim and pa respondents for each demographic variable as control variates in our regressions. We find that the differences in age, end grade (highest grade completed) and income have a significant effect on $PAGO_t^{\text{pa}}$, while the other characteristics are mostly insignificant (see the full results in Appendix B.1). Correcting for differences in age, end grade or income, the effect of $PEXP_t^{\text{prelim}}$ becomes stronger and more significant. The same holds when we correct for all three of them. The Wald statistics also still reject that $PAGO_t^{\text{prelim}}$ is an unbiased predictor.

Table 6b shows that $PAGO_t^{\text{pa}}$ is also positively related to the preliminary expectations about the development of business conditions for the next year, measured by BUS1Y. However, the effect is about half of what we observe for PEXP with coefficients around 0.10, and significance levels around 10%. Of course, the conceptual differences between the BUS1Y and PAGO questions are larger than between PAGO and PEXP. PAGO and PEXP both concern a respondent's financial position, PAGO the past yearly change and PEXP the future yearly change. The link between the development in business conditions and changes in ones personal financial position are clearly weaker. The Wald tests indicate strong support against $PAGO_t^{\text{prelim}}$ being an unbiased predictor.

The results when using the 5-year expectations regarding business conditions BUS5Y in Table 6c are weaker than those based on the 1-year expectations. This difference may be explained by 5-year expectations being conceptually more removed from past changes in financial positions than 1-year expectations. However, the Wald tests show that the unbiasedness of $PAGO_t^{\text{prelim}}$ as a predictor of $PAGO_t^{\text{pa}}$ is rejected also for this case.

In Table 6d we show how the three forward looking variables together are related to $PAGO_t^{\text{pa}}$. The effect of PEXP is strongest. The coefficients are similar to those in Table 6a and significant between the 5 and 10% level. The effect of BUS1Y is still positive, with coefficients as in Table 6b, but significance is lost. The coefficients for BUS5Y change sign and have large standard errors, indicating that BUS5Y does not contribute much compared to PEXP and BUS1Y. We reject that $PAGO_t^{\text{prelim}}$ is an unbiased predictor of $PAGO_t^{\text{pa}}$, but we find only weak evidence against the hypothesis that the coefficients on PEXP, BUS1Y and BUS5Y are jointly zero.

We conclude that we find evidence for irrational herding. The sentiment about the future of one group of respondents has an effect on assessment of the past by another group of respondents, beyond what can be attributed to the assessment of the past of this first group. The effect is stronger, when the sentiment about the future is conceptually more related to the assessment of the past. When we correct for differences in the composition of the groups, these results do not disappear, but become stronger.

5.3 Feedback loop

The system-1 channel with which future expectations influence assessments of the past give rise to a feedback loop. Suppose that the prelim-respondents become more positive about the future, for example because they receive good news. Of course, this good news will also make the pa-respondents more positive about the future. However, because of the herding effect that we find, the pa-respondents will also become more positive about the past. So, we will see a knock-on effect on consumer confidence as a whole. Respondents in the next period will include this information in their assessments of the past and the future, which will then also rise more than what could be expected purely in system 2.

To gauge the impact of the feedback loop, we set up a specific impulse response analysis in a VAR-setting. We use a standard VAR(1) to model the joint evolution of the final values of PAGO and the k forward looking variables $\boldsymbol{x}_t$,

$$\boldsymbol{y}_{t+1} = \boldsymbol{\psi} + \boldsymbol{\Phi} \boldsymbol{y}_t + \boldsymbol{\eta}_{t+1}, \quad \boldsymbol{\eta} \sim \mathrm{N}(\boldsymbol{0}, \boldsymbol{\Sigma}), \tag{13}$$

where $\boldsymbol{y}_t = (PAGO_t^{\text{final}}, (\boldsymbol{x}_t^{\text{final}})')'$, $\boldsymbol{\psi}$ is a vector of size $k+1$, $\boldsymbol{\Phi}$ is a square matrix of size $k+1$. The final values are a weighted sum of the prelim and np values,

$$\begin{pmatrix} PAGO_t^{\text{final}} \\ \boldsymbol{x}_t^{\text{final}} \end{pmatrix} = (1 - w_t) \begin{pmatrix} PAGO_t^{\text{prelim}} \\ \boldsymbol{x}_t^{\text{prelim}} \end{pmatrix} + w_t \begin{pmatrix} PAGO_t^{\text{pa}} \\ \boldsymbol{x}_t^{\text{pa}} \end{pmatrix}, \tag{14}$$

where w_t gives the proportion of pa-respondents in month t.

We assume that a shock $\Delta \boldsymbol{x}_t^{\text{prelim}}$ occurs in the prelim values of the forward looking variable $\boldsymbol{x}$ at time t, which is added to the conditional expectation based on the information at time $t-1$, $\boldsymbol{x}_t = \mathrm{E}\big[\boldsymbol{x}_t^{\text{prelim}} \big| \boldsymbol{y}_{t-1}\big] + \Delta \boldsymbol{x}_t^{\text{prelim}}$. The prelim value of PAGO does not encounter a shock, $\Delta PAGO_t^{\text{prelim}} = 0$, so $PAGO_t^{\text{prelim}} = E\big[PAGO_t^{\text{prelim}} \big| \boldsymbol{y}_{t-1}\big]$. Following the standard approach for VAR models (see Lütkepohl, 2005; Koop et al., 1996), we define the impulse response function of the VAR to this shock for horizon h as

$$\begin{aligned} IR(h, \Delta \boldsymbol{x}_t^{\text{prelim}}, \boldsymbol{y}_{t-1}) &= \mathrm{E}[\boldsymbol{y}_{t+h} | \Delta \boldsymbol{x}_t^{\text{prelim}}, \Delta PAGO_t^{\text{prelim}} = 0, \boldsymbol{y}_{t-1}] - \mathrm{E}[\boldsymbol{y}_{t+h} | \boldsymbol{y}_{t-1}] \\ &= \boldsymbol{\Phi}^h \big(\mathrm{E}[\boldsymbol{y}_t | \Delta \boldsymbol{x}_t^{\text{prelim}}, \Delta PAGO_t^{\text{prelim}} = 0, \boldsymbol{y}_{t-1}] - \mathrm{E}[\boldsymbol{y}_t | \boldsymbol{y}_{t-1}] \big). \end{aligned} \quad (15)$$

The first term in this multiplication captures the propagation of the shock h months forward. The second term captures the effect of the shock in the prelim-values on the final values at the end of the month.

Our interest focuses on the second term, because the expectation conditional on the shock, $\mathrm{E}[\boldsymbol{y}_{t+h} | \Delta \boldsymbol{x}_t^{\text{prelim}}, \Delta PAGO_t^{\text{prelim}} = 0, \boldsymbol{y}_{t-1}]$, depends on the system in which they are evaluated (which we denote by subscripts S1 and S2). In both systems, the pa-respondents will update their expectations because of the shock. We assume that the updating follows from the standard multivariate linear model, which is an extension of Equation (12),

$$PAGO_t^{\text{pa}} = \alpha_1 + \beta_1 PAGO_t^{\text{prelim}} + \boldsymbol{\gamma}_1' \boldsymbol{x}_t^{\text{prelim}} + \boldsymbol{\delta}_1' \boldsymbol{z}_t + \varepsilon_{1,t} \quad (16)$$

$$\boldsymbol{x}_t^{\text{pa}} = \boldsymbol{\alpha}_2 + \boldsymbol{\beta}_2 PAGO_t^{\text{prelim}} + \boldsymbol{\gamma}_2 \boldsymbol{x}_t^{\text{prelim}} + \boldsymbol{\delta}_2 \boldsymbol{z}_t + \boldsymbol{\varepsilon}_{2,t}, \quad (17)$$

where $\boldsymbol{\alpha}_2$ and $\boldsymbol{\beta}_2$ are vectors of size k, $\boldsymbol{\gamma}_2$ is a $k \times k$ matrix, and $\boldsymbol{\delta}_2$ a $k \times m$ matrix that gives the effect of the covariates. In system 2, the restriction $\boldsymbol{\gamma}_1 = \mathbf{0}$ applies, contrary to system 1. Because the forward looking variables $\boldsymbol{x}_t^{\text{np}}$ can be rationally influenced by both $PAGO_t^{\text{prelim}}$ and $\boldsymbol{x}_t^{\text{prelim}}$, there are no coefficient restrictions in Equation (17) in either system 1 or 2.

The expected effect of the shock on $PAGO_t^{\text{pa}}$ in system 1 follows from Equation (16) as

$$\mathrm{E}_{\text{S1}}\big[PAGO_t^{\text{pa}} | \Delta \boldsymbol{x}_t^{\text{prelim}}, \Delta PAGO_t^{\text{prelim}} = 0, \boldsymbol{y}_{t-1}\big] - \mathrm{E}_{\text{S1}}\big[PAGO_t^{\text{pa}} | \boldsymbol{y}_{t-1}\big] = \boldsymbol{\gamma}_1' \Delta \boldsymbol{x}_t^{\text{prelim}}. \quad (18)$$

Because $\boldsymbol{\gamma}_1 = 0$ in system 2, the expected effect in system 2 is zero,

$$\mathrm{E}_{\text{S2}}\big[PAGO_t^{\text{pa}} | \Delta \boldsymbol{x}_t^{\text{prelim}}, \Delta PAGO_t^{\text{prelim}} = 0, \boldsymbol{y}_{t-1}\big] - \mathrm{E}_{\text{S2}}\big[PAGO_t^{\text{pa}} | \boldsymbol{y}_{t-1}\big] = 0. \quad (19)$$

In both systems, the effect on $\boldsymbol{x}_t^{\text{np}}$ is given by

$$\begin{aligned} &\mathrm{E}_{\text{S1}}\big[\boldsymbol{x}_t^{\text{pa}} | \Delta \boldsymbol{x}_t^{\text{prelim}}, \Delta PAGO_t^{\text{prelim}} = 0, \boldsymbol{y}_{t-1}\big] - \mathrm{E}_{\text{S1}}\big[\boldsymbol{x}_t^{\text{pa}} | \boldsymbol{y}_{t-1}\big] = \\ &\mathrm{E}_{\text{S2}}\big[\boldsymbol{x}_t^{\text{pa}} | \Delta \boldsymbol{x}_t^{\text{prelim}}, \Delta PAGO_t^{\text{prelim}} = 0, \boldsymbol{y}_{t-1}\big] - \mathrm{E}_{\text{S2}}\big[\boldsymbol{x}_t^{\text{pa}} | \boldsymbol{y}_{t-1}\big] = \boldsymbol{\gamma}_2 \Delta \boldsymbol{x}_t^{\text{prelim}}. \end{aligned} \quad (20)$$

With Equation (14) the effect on the final values can be calculated.

We first investigate the feedback loop when the loop runs via only one of the forward-looking variables. We report the estimated coefficients of Equations (13) and (17) in Tables B.4 and B.5 in Appendix B.1. In Figure 1 we show how a shock of 1 in one of the forward looking variables impacts PAGO from the month of the shock ($h = 0$) up to 60 months in the future ($h = 60$). We show the results based on the estimates for the longest series here. The estimates for the shorter series do not much differ, so they will lead to similar results. Because the weights of the prelim versus pa-respondents varies over time, we use its average value in Equation (14). The dotted lines in panels (a–c) give the effect that the shock has in system 2. Because of the restriction in Equation (19), the effect starts at zero, but becomes positive in the next month. For all three variables, peaks of about 0.26 (PEXP and BUS1Y), and 0.23 (BUS5Y) are reached after about 6 months. Thereafter, the shocks slowly die out. The solid lines lie above the dotted line and show the knock-on effect that the shock has in system 1. Following Equations (14) and (18), the lines start above zero because the γ_1-coefficients reported in the first column of each panel of Table 6 are positive. The shock then propagates through the system and reaches maxima of 0.30 (PEXP), 0.28 (BUS1Y) and 0.25 (BUS5Y). Though these effects may seem small, we show in panel d that the increase of the impact of the shock in system 1 relative to system 2 is sizable, in particular in the first months. Shocks in PEXP have an effect that is more than 15% stronger in the first six months. As we also showed in Table 6, the effects of shocks in BUS1Y and BUS5Y are smaller, but still exceed 6-7% over that horizon.

[Figure 1 about here.]

Next, we turn to the feedback loop when the effect can run via the three forward-looking variables combined. Our impulse response analysis differs slightly from the previous one, as we need to take into account that shocks to the three variables are correlated. Although it is possible to determine how a shock to, say, $BUS1Y1Y_t^{\text{prelim}}$ only propagates through the system under the assumption that $PEXP_t^{\text{prelim}}$ and $BUS1Y5Y_t^{\text{prelim}}$ do not encounter a shock, that situation is not very realistic. Instead, we follow the framework of Koop et al. (1996) and determine for a given shock in forward-looking variable i, the expected shock in the other two forward-looking variables,

$$\begin{aligned}&\mathrm{E}[\Delta \boldsymbol{x}_t | \Delta x_{it}^{\text{prelim}}, \Delta PAGO_t^{\text{prelim}} = 0, \boldsymbol{y}_{t-1}]\\ =&\,\mathrm{E}[\boldsymbol{x}_t^{\text{prelim}} | \Delta x_{it}^{\text{prelim}}, \Delta PAGO_t^{\text{prelim}} = 0, \boldsymbol{y}_{t-1}] - \mathrm{E}[\boldsymbol{x}_t^{\text{prelim}} | \boldsymbol{y}_{t-1}],\end{aligned} \tag{21}$$

and then determine the propagation of the shocks through the system. We again use a standard linear model to determine the relation between $\boldsymbol{x}_t$ on $\boldsymbol{y}_{t-1}$ with the assumption of normally distributed error terms. We use the covariance matrix of the error terms to determine the expected shocks in Equation (21). We report the estimation results in Table B.6.

The results of this impulse response analysis in Figure 2 confirm our results for the bivariate analyses. The impulse responses are generally a bit smaller, and the same holds for the difference between system 1 and system 2. Table 6d also shows that the herding effect is less clear-cut when it can run via PEXP, BUS1Y and BUS5Y combined. Still, Figure 2d shows that the impact of a shock in system 1 relative to system 2 is more than 10% stronger in the first six months for PEXP, and more than 5% for BUS1Y and BUS5Y for that horizon. So, also this analysis shows how herding in system 1 can produce a feedback loop.

[Figure 2 about here.]

6 Conclusion

In this paper we show the presence of cognitive biases in the Index of Consumer Sentiment of the University of Michigan. First, respondents relate the change in their financial position over the last year more to detrimental extremes in financial and macroeconomic state variables than to the total monthly changes. Second, their assessment of past changes can be predicted by the expectation about future changes of other respondents beyond how they assessed past changes. The predictability of expected future changes increases when we correct for systematic demographic differences between the groups of respondents.

The cognitive biases we find are in line with the decision-making framework of Tversky and Kahneman (1974) where agents make quick intuitive assessments under system 1, instead of more reasoned assessments under system 2. Our first finding provides evidence of the peak part of the peak-end rule, though we find no evidence of the end-part. Instead of a detailed consideration of changes in their financial position, agents use the peak-end rule as a heuristic, where in our case the worst change is substituted for the total change. The second finding is a form of irrational herding. This result can be interpreted as the anchoring heuristic of system 1.

Our findings show that the cognitive biases are not restricted to individual behavior, but also affect an important economic indicator such as the ICS. This has two important implications. First, it means that the ICS is more than just a summary of macro information, as it adds the perspective of consumers that is not present in more objective macro variables. Second, because ICS predicts consumer spending, these cognitive effects that are present in the ICS can be expected to influence consumer spending, too.

Our findings also point at the presence of feedback loops. Past changes form the expectations for the future. The result that future expectations influence past assessments in turn, means that consumer confidence is susceptible to upward or downward feedback loops.

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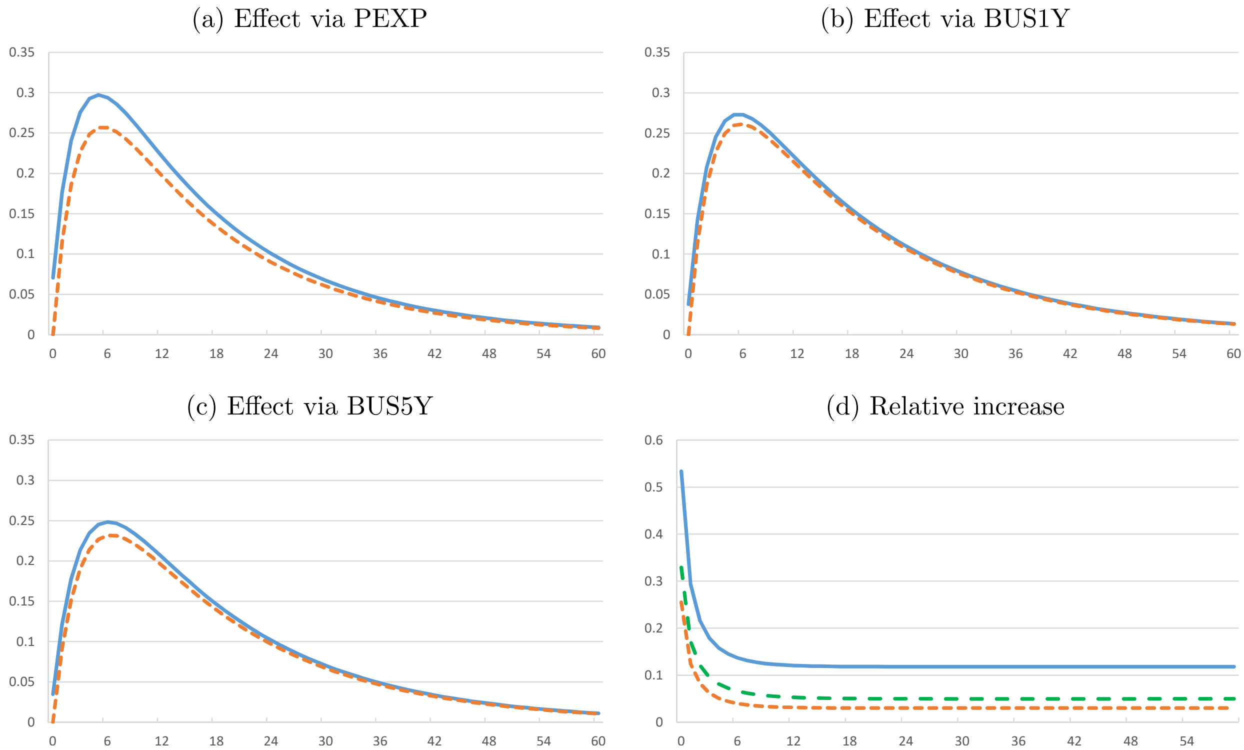
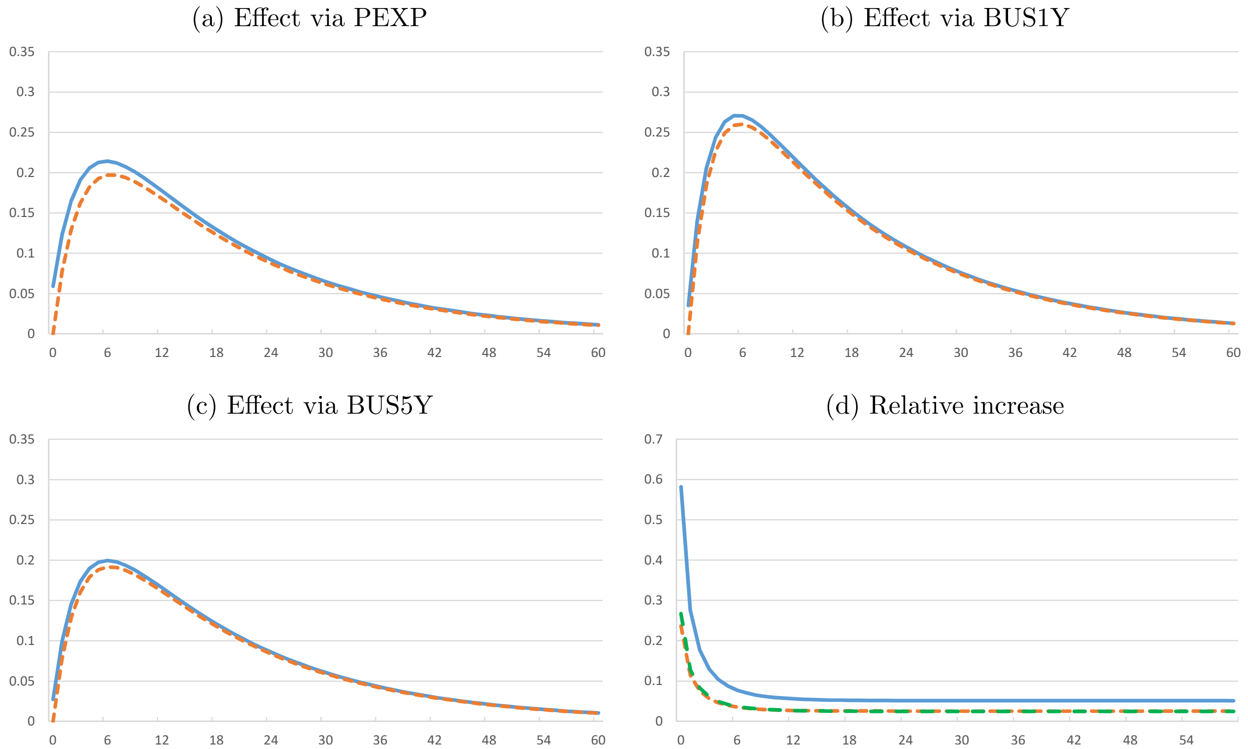
Figure 1: Impulse Response Analysis, bivariate models



This figure shows tne impulse response functions of the final values of PAGO for different horizons based on a shock of 1 in one of the forward-looking variables (PEXP, BUS1Y and BUS5Y in panels a to c). The impulse response functions follow from Equations (15) and (20) combined with Equation (18) in system 1 (solid blue line) or with Equation (19) in system 2 (orange dotted line). The esimates for $\boldsymbol{\Phi}$ in Equation (15) are reported in Table B.4(a), the estimates for γ_1 in Table 6, and the estimates for γ_2 in Table B.5, all in the columns corresponding with the np-series. Panel d gives the relative increase of the effect of the shock in system 1 compared to system 2 for each forward looking variable (PEXP: solid blue, BUS1Y: dotted orange and BUS5Y: dashed green).

Figure 2: Impulse Response Analysis, multivariate models



This figure shows tne impulse response functions of the final values of PAGO for different horizons based on a shock of 1 in one of the forward-looking variables (PEXP, BUS1Y and BUS5Y in panels a to c). We take the correlation between the shocks to the variables into account, and calculate the expected shocks in the other two variables as in Equation (21), assuming a linear model for the relation between $\boldsymbol{x}_t^{\text{prelim}}$ and $\boldsymbol{y}_{t-1}$ with normally distributed error terms. Estimation results for this model are in Table B.6. The (expected) shocks for the different panels are $(1, 0.576, 0.346)'$, $(0.136, 1, 0.513)'$ and $(0.132, 0.833, 1)'$. The impulse response functions follow from Equations (15) and (20) combined with Equation (18) in system 1 (solid blue line) or with Equation (19) in system 2 (orange dotted line). The esimates for $\boldsymbol{\Phi}$ in Equation (15) are reported in Table B.4(a), the estimates for γ_1 in Table 6, and the estimates for γ_2 in Table B.5(d), all in the columns corresponding with the np-series. Panel d gives the relative increase of the effect of the shock in system 1 compared to system 2 for each forward looking variable (PEXP: solid blue, BUS1Y: dotted orange and BUS5Y: dashed green).

Table 1: Summary statistics for ICS and its constituting variables

(a) Marginal distribution

	ICS	PAGO	PEXP	BUS	BUS5Y	DUR
Mean	85.1	105.8	121.2	100.1	89.5	144.4
Median	88.3	109.0	123.5	103.5	90.0	148.0
Minimum	51.7	58.0	90.0	31.0	40.0	77.0
	May-80	Aug-09	Apr-79	May-80	Jul-79	May-80
Maximum	112.0	142.0	145.0	165.0	136.0	182.0
	Jan-00	Feb-98	Feb-98	Jan-00	Feb-00	May-99
Std. Dev.	12.9	16.7	10.9	29.9	18.4	19.6

(b) Correlation

	ICS	PAGO	PEXP	BUS	BUS5Y	DUR
ICS	1					
PAGO	0.92	1				
PEXP	0.87	0.78	1			
BUS	0.96	0.84	0.81	1		
BUS5Y	0.91	0.74	0.84	0.88	1	
DUR	0.90	0.86	0.70	0.81	0.72	1

This table gives summary statistics for the ICS and its constituting series. Below the minimum and maximum values for the different series, we report the date of occurrence. The sample period is from January 1978 to December 2014 (444 months).

Table 2: Summary Statistics of Explanatory Variables and their Peak and End Rule Transformations

(a) Means and standard deviations

		Financial					Macro				
		SP500	LABI	UST3M	UST10Y	HPIQ	CPI	GNPQ	NFP	UNEMP	PCE
	change in	log	log	level	level	log	log	log	log	level	log
	frequency	m	m	m	m	q	m	q	m	m	m
ra	mean	8.04	0.37	-0.14	-0.13	4.16	3.71	6.16	1.43	-0.02	5.81
	stdev	16.17	5.57	1.87	1.33	4.27	2.68	2.85	1.92	1.08	2.39
sp	mean	6.92	2.26	0.42	0.44	1.81	0.70	2.49	0.45	0.29	1.63
	stdev	2.44	1.78	0.58	0.28	1.01	0.30	1.21	0.27	0.16	0.60
mp	mean	17.88	5.04	1.10	1.01	4.81	3.87	6.23	1.89	0.64	6.06
	stdev	8.74	3.71	1.57	0.80	3.14	2.55	2.72	1.26	0.76	2.14
sb	mean	-6.89	-2.37	-0.56	-0.49	0.31	-0.10	0.72	-0.20	-0.28	-0.45
	stdev	4.76	1.38	0.90	0.37	1.34	0.38	0.76	0.28	0.11	0.56
mb	mean	-11.39	-4.71	-1.26	-1.14	0.09	-0.19	0.77	-0.49	-0.63	-0.54
	stdev	11.07	3.71	1.74	0.85	2.05	0.64	0.82	0.88	0.45	0.78
end	mean	0.69	0.04	-0.01	-0.01	1.02	0.30	1.51	0.12	-0.003	0.48
	stdev	4.41	1.57	0.49	0.32	1.21	0.34	1.01	0.25	0.197	0.66

(b) Correlations of the Peak and End Rule Transformations with the Rational Rule

	SP500	LABI	UST3M	UST10Y	HPIQ	CPI	GNPQ	NFP	UNEMP	PCE
sp	0.12	0.09	0.22	0.43	0.89	0.74	0.81	0.74	0.64	0.63
mp	0.67	0.55	0.49	0.72	0.94	0.98	0.99	0.93	0.91	0.96
sb	0.52	0.39	0.27	0.30	0.95	0.64	0.74	0.69	0.54	0.23
mb	0.79	0.70	0.51	0.66	0.92	0.54	0.79	0.84	0.72	0.40
end	0.30	0.34	0.32	0.34	0.85	0.64	0.67	0.60	0.43	0.33

This table shows summary statistics of the series of the explanatory variables that have been transformed according to different rules, given in the rows. The rational rule is given in Equation (5), the extreme rules in Equation (6) and the end rule in Equation (7). All rules use the observations of the past year. In panel (a) we report the mean and standard deviation of each transformed series. In panel (b) we report for each variable the correlation of the series transformed by the peak and end rules with the series according to the rational rule. In the top op panel (a) we indicate whether the base series are differences in logs or in levels, and whether their frequency is monthly (m) or quarterly (q). The first observation for each transformed series is available at the start of January 1978. For PCE, the first observation pertains to January 1981. See Table A.2 for more information on the source and nature of the explanatory variables.

Table 3: Tests Results of the Peak and End Rules based on Financial Variables

(a) Changes in the log of the S&P500

rule	ra		sp			mp			sb			mb			end		
g^{ra}	0.35**	0.31**		0.36**	0.37**		0.53***	0.69***		0.33*	0.37**		0.09	−0.15		0.35**	0.32**
	(0.14)	(0.16)		(0.14)	(0.18)		(0.17)	(0.25)		(0.17)	(0.18)		(0.23)	(0.22)		(0.14)	(0.16)
g^r			−0.48	−0.77	−0.84	0.15	−0.50	−0.77*	0.67	0.08	−0.90	0.58***	0.48	1.20***	0.29	−0.09	−0.06
			(0.69)	(0.64)	(1.12)	(0.28)	(0.34)	(0.41)	(0.67)	(0.65)	(1.19)	(0.20)	(0.36)	(0.41)	(0.27)	(0.18)	(0.18)
vol.		−0.24			0.04			0.48			−0.87			1.12*			−0.23
		(0.48)			(0.73)			(0.54)			(0.85)			(0.61)			(0.48)
R^2	0.11	0.11	0.00	0.12	0.12	0.00	0.15	0.16	0.03	0.11	0.12	0.15	0.15	0.18	0.00	0.11	0.11

(b) Changes in the log of the Lehman Aggregate Bond Index

rule	ra		sp			mp			sb			mb			end		
g^{ra}	0.03	−0.07		0.09	0.03		0.46	0.13		−0.19	0.03		−0.51	0.03		0.06	−0.06
	(0.36)	(0.31)		(0.32)	(0.37)		(0.38)	(0.52)		(0.33)	(0.35)		(0.39)	(0.41)		(0.38)	(0.31)
g^r			−2.04***	−2.07***	−1.25	−0.77*	−1.15**	−0.44	2.05	2.35	−1.54	0.64	1.17*	−0.25	−0.24	−0.32	−0.13
			(0.76)	(0.74)	(3.04)	(0.46)	(0.49)	(0.95)	(1.44)	(1.52)	(2.95)	(0.53)	(0.63)	(0.88)	(0.52)	(0.44)	(0.39)
vol.		−1.35**			−0.57			−0.87			−2.01*			−1.56*			−1.34**
		(0.60)			(2.24)			(1.28)			(1.19)			(0.91)			(0.60)
R^2	0.00	0.04	0.05	0.04	0.04	0.03	0.04	0.04	0.03	0.03	0.04	0.02	0.03	0.04	0.00	0.00	0.04

(c) Changes in the 3-month T-Bill rate

rule	ra		sp			mp			sb			mb			end		
g^{ra}	1.33	1.13		1.94**	2.18*		2.80***	2.41		0.66	1.61		−0.18	0.10		1.28	1.12
	(1.12)	(0.96)		(0.90)	(1.31)		(0.99)	(1.88)		(1.04)	(1.31)		(1.04)	(1.37)		(1.17)	(0.99)
g^r			−7.64***	−9.02***	−11.71	−1.89*	−3.54***	−2.73	5.47***	5.10***	−4.93	3.09***	3.19***	2.50	2.11	0.53	0.20
			(2.27)	(2.48)	(8.87)	(1.11)	(1.04)	(3.23)	(1.11)	(1.28)	(5.72)	(0.80)	(0.86)	(3.32)	(1.75)	(1.55)	(1.02)
vol.		−3.50***			1.17			−0.87			−6.59*			−0.79			−3.50***
		(0.88)			(3.64)			(2.73)			(3.92)			(3.33)			(0.88)
R^2	0.02	0.10	0.07	0.11	0.11	0.03	0.10	0.10	0.08	0.09	0.10	0.10	0.10	0.10	0.00	0.02	0.10

This table shows the results of regressions of $PAGO_t$ on changes of financial variables over the past year, $\Delta x_{j,t-12}, \ldots, \Delta x_{j,t-1}$ that have been transformed based on different rules. In each panel a different financial variable is used. The column headings indicate which rule is used. The row g^{ra} contains the coefficient estimates for the rational rule of Equation (5). The row g^r contains the coefficient estimates for one of the peak-end rules in Equations (6) and (7) as indicated by the column. We report standard errors in parentheses based on Newey and West (1987) with a Bartlett kernel and bandwidth value of 12. The abbreviations stand for ra: rational; sp: single peak; mp: multi-period peak; sb: single bottom; mb: multi-period bottom. Superscripts ***,**,* indicate significance at the 1%, 5% and 10% level. The rows "R^2" give the adjusted R^2. The sample period is from January 1978 to December 2014 ($T = 444$).

Table 3: Tests Results of the Peak and End Rules based on Financial Variables – *continued*

(d) Changes in the 10-year bond yield

rule	ra		sp			mp			sb			mb			end		
g^{ra}	−0.31	−0.15		0.91	−1.03		2.02	−2.72		−1.66	−3.83**		−2.55	2.07		−0.43	−0.23
	(1.48)	(1.27)		(1.30)	(1.79)		(1.74)	(2.18)		(1.27)	(1.67)		(1.64)	(2.43)		(1.55)	(1.33)
g^{r}			−11.55*	−13.42**	10.64	−2.89	−5.31*	6.11	14.84***	16.63***	39.45**	2.63	5.26**	−4.97	0.92	1.53	0.99
			(6.44)	(6.52)	(19.33)	(2.45)	(2.97)	(4.88)	(4.23)	(4.08)	(15.77)	(2.13)	(2.29)	(4.85)	(2.69)	(2.51)	(2.24)
vol.		−8.18***			−12.68			−13.71***			16.08			−13.60**			−8.15***
		(2.46)			(8.16)			(4.34)			(10.68)			(5.84)			(2.46)
R^2	0.00	0.06	0.03	0.04	0.07	0.02	0.03	0.07	0.10	0.12	0.15	0.02	0.04	0.07	0.00	0.00	0.06

(e) Changes in the log of the House Price Index of the US. Federal Housing Finance Agency

rule	ra		sp			mp			sb			mb			end		
g^{ra}	1.88***	0.76**		6.07***	2.67***		6.75***	2.29**		−3.99***	0.33		−3.08***	−0.73		1.66*	0.65
	(0.63)	(0.37)		(0.52)	(0.87)		(0.64)	(0.93)		(1.19)	(0.61)		(0.83)	(0.77)		(0.89)	(0.54)
g^{r}			2.89	−19.97***	−7.54*	1.54*	−7.07***	−1.99	7.58***	19.71***	1.65	5.32***	11.24***	4.03**	5.89***	0.88	0.44
			(2.80)	(2.80)	(3.92)	(0.91)	(1.15)	(1.25)	(1.52)	(3.49)	(2.45)	(0.61)	(1.51)	(1.60)	(1.67)	(1.69)	(1.18)
vol.		−14.58***			−10.28***			−12.43***			−13.77***			−10.71***			−14.57***
		(1.80)			(2.35)			(2.40)			(2.16)			(2.47)			(1.79)
R^2	0.23	0.58	0.03	0.54	0.59	0.08	0.44	0.58	0.37	0.47	0.57	0.43	0.52	0.59	0.18	0.23	0.57

See Table note on the previous page.

Table 4: Tests Results of the Peak and End Rules based on Macro Variables

(a) Changes in the log of CPI

rule	ra		sp			mp			sb			mb			end		
g^{ra}	−1.51*	−1.72***		1.28	−3.41**		13.72***	5.28*		−4.31***	−3.85***		−3.61***	−2.76***		−1.70*	−1.73***
	(0.84)	(0.48)		(1.42)	(1.63)		(1.51)	(2.97)		(0.68)	(1.32)		(0.52)	(0.85)		(1.00)	(0.53)
g^r			−25.69***	−34.21***	19.64	−2.18***	−16.33***	−7.44**	11.49	31.13***	25.60*	8.01**	16.25***	8.83	−6.21	2.37	0.10
			(5.50)	(13.19)	(18.16)	(0.53)	(1.74)	(3.19)	(8.04)	(5.13)	(13.85)	(3.43)	(1.95)	(6.12)	(6.45)	(5.18)	(2.78)
vol.		−19.79***			−27.73***			−13.42***			−3.85			−10.06			−19.79***
		(3.95)			(8.06)			(4.84)			(9.44)			(8.35)			(3.94)
R^2	0.06	0.33	0.21	0.22	0.34	0.11	0.29	0.35	0.07	0.35	0.35	0.09	0.33	0.34	0.01	0.06	0.33

(b) Changes in the log of the GNP

rule	ra		sp			mp			sb			mb			end		
g^{ra}	1.55	1.75		1.57	0.56		16.82***	16.82***		0.29	−1.11		−0.08	−4.88*		1.27	1.41
	(1.03)	(1.10)		(1.46)	(1.28)		(3.35)	(3.88)		(1.11)	(1.64)		(1.18)	(2.62)		(1.04)	(1.08)
g^r			2.96	−0.06	4.37	1.44	−16.13***	−16.12***	7.15**	6.33	11.36**	6.94**	7.17*	23.19***	3.59	1.18	1.51
			(2.24)	(2.84)	(3.12)	(1.07)	(4.18)	(4.81)	(3.51)	(3.88)	(4.86)	(3.12)	(3.80)	(7.92)	(2.37)	(1.67)	(1.59)
vol.		−1.73			−4.45			−0.01			3.54			9.95**			−1.92
		(2.47)			(2.86)			(2.38)			(3.07)			(4.97)			(2.51)
R^2	0.07	0.07	0.04	0.07	0.09	0.05	0.14	0.14	0.10	0.10	0.11	0.11	0.11	0.16	0.05	0.07	0.08

(c) Changes in the log of nonfarm payrolls

rule	ra		sp			mp			sb			mb			end		
g^{ra}	4.82***	4.75***		6.83***	5.98***		8.11***	6.26***		3.99***	6.18***		2.83	4.26**		4.32***	4.13***
	(1.00)	(0.95)		(1.24)	(1.48)		(1.82)	(2.13)		(1.27)	(1.34)		(1.79)	(1.89)		(1.00)	(0.94)
g^r			17.06	−19.33**	−11.54	6.03***	−5.43	−2.47	27.42***	8.31	−14.84	10.36***	5.15	1.28	26.41***	6.48	7.98**
			(10.57)	(9.48)	(12.31)	(1.85)	(3.31)	(3.66)	(7.02)	(7.28)	(12.16)	(1.43)	(3.20)	(3.75)	(6.80)	(4.04)	(3.97)
vol.		−12.82*			−7.23			−10.64			−21.70*			−11.46			−13.32**
		(6.83)			(8.23)			(7.46)			(11.28)			(7.79)			(6.52)
R^2	0.30	0.35	0.07	0.35	0.35	0.20	0.33	0.35	0.21	0.31	0.36	0.30	0.32	0.34	0.15	0.31	0.35

This table shows the results of regressions of $PAGO_t$ on changes of macro variables over the past year, $\Delta x_{j,t-12}, \ldots, \Delta x_{j,t-1}$ that have been transformed based on different rules. In each panel a different variable is used. The column headings indicate which rule is used. The row g^{ra} contains the coefficient estimates for the rational rule of Equation (5). The row g^r contains the coefficient estimates for one of the peak-end rules in Equations (6) and (7) as indicated by the column. We report standard errors in parentheses based on Newey and West (1987) with a Bartlett kernel and bandwidth value of 12. The abbreviations stand for ra: rational; sp: single peak; mp: multi-period peak; sb: single bottom; mb: multi-period bottom. Superscripts $^{***}, ^{**}, ^{*}$ indicate significance at the 1%, 5% and 10% level. The rows "R^2" give the adjusted R^2. The sample period is from January 1978 to December 2014 ($T = 444$).

Table 4: Tests Results of the Peak and End Rules based on Macro Variables – ***continued***

(d) Changes in the unemployment rate

rule	ra		sp			mp			sb			mb			end		
g^{ra}	−8.33***	−6.93***		−6.90***	−8.38***		0.14	−1.71		−9.54***	−6.03***		−12.40***	−10.50***		−8.17***	−6.63*
	(1.43)	(1.63)		(1.76)	(1.74)		(3.37)	(3.25)		(1.50)	(1.96)		(1.78)	(2.25)		(1.39)	(1.60)
g^r			−43.39***	−14.69	23.73	−13.07***	−13.26***	−9.15**	−27.93	21.82	−11.40	−7.89*	13.71***	9.92*	−21.23***	−1.96	−3.64
			(12.71)	(12.45)	(20.57)	(1.56)	(4.42)	(4.62)	(22.55)	(17.88)	(23.42)	(4.04)	(5.13)	(5.33)	(7.40)	(3.44)	(3.28)
vol.		−21.33***			−34.59**			−11.85			−25.41**			−11.93			−21.61*
		(7.10)			(13.97)			(7.33)			(10.70)			(7.45)			(7.09)
R^2	0.29	0.34	0.18	0.30	0.35	0.35	0.35	0.36	0.03	0.30	0.34	0.04	0.35	0.36	0.06	0.29	0.34

(e) Changes in the log of personal consumption expenditures

rule	ra		sp			mp			sb			mb			end		
g^{ra}	3.69***	4.02***		3.92***	3.65**		9.44***	9.38***		3.39***	2.87*		2.89***	1.47		3.70***	4.02*
	(1.07)	(1.10)		(1.49)	(1.50)		(1.51)	(1.82)		(1.06)	(1.61)		(1.10)	(1.78)		(1.08)	(1.10)
g^r			8.44***	−1.45	3.29	3.51***	−6.66***	−6.57**	8.92*	5.67	9.17	9.63***	6.09**	11.53**	3.91**	−0.05	0.02
			(3.10)	(3.73)	(5.96)	(1.32)	(2.37)	(3.11)	(5.32)	(3.71)	(6.74)	(2.73)	(2.60)	(4.99)	(1.92)	(1.03)	(0.99)
vol.		−3.04			−4.50			−0.12			3.10			6.56			−3.04
		(2.36)			(4.12)			(2.77)			(4.99)			(5.19)			(2.36)
R^2	0.28	0.29	0.09	0.28	0.30	0.20	0.33	0.33	0.09	0.31	0.31	0.20	0.34	0.37	0.02	0.28	0.29

See Table note on the previous page.

Table 5: End rule, contemporaneous analysis

(a) Financial Variables

	log S&P500			log LABI			UST3m			UST10y		
g^{ra}	0.33**		0.34**	0.00		0.03	1.34		0.03	−0.25		0.72
	(0.14)		(0.15)	(0.37)		(0.39)	(1.11)		(1.76)	(1.49)		(2.58)
g^{end}		0.22	−0.15		−0.26	−0.30		1.67	1.34		0.30	−0.31
		(0.26)	(0.18)		(0.51)	(0.51)		(1.71)	(1.16)		(2.73)	(1.56)
R^2	0.10	0.00	0.10	0.00	0.00	0.00	0.02	0.00	0.02	0.00	0.00	0.00

(b) Macro Variables

	log CPI			log NFP			UNEMP			log PCE		
g^{ra}	−1.43*		−1.64	4.96***		4.60***	−8.35***		−8.37***	3.64***		3.67***
	(0.86)		(1.02)	(0.98)		(1.00)	(1.45)		(1.41)	(1.10)		(1.11)
g^{end}		−5.74	2.51		25.87***	4.69		−19.52***	0.16		3.81**	−0.28
		(6.31)	(5.01)		(6.78)	(4.04)		(7.38)	(3.33)		(1.82)	(1.06)
R^2	0.05	0.01	0.05	0.32	0.15	0.32	0.29	0.05	0.29	0.27	0.02	0.27

This table shows the results of regressions of $PAGO_t$ on changes of financial variables over the past 11 months and the current month, $\Delta x_{j,t-11}, \ldots, \Delta x_{j,t}$ that have been transformed based on the rational and the end-rule. The column headers indicate which financial (panel a) and macro variables (panel b) are considered. The row g^{ra} contains the coefficient estimates for the rational rule of Equation (5). The row g^{end} contains the coefficient estimates for the end rules in Equation (7). We report standard errors in parentheses based on Newey and West (1987) with a Bartlett kernel and bandwidth value of 12. Superscripts ***,**,* indicate significance at the 1%, 5% and 10% level. The rows "R^2" give the adjusted R^2. The sample period is from January 1978 to December 2014 ($T = 444$).

Table 6: Test of the Herding Effect

(a) Effect via PEXP

	$PAGO^{\mathrm{np}}$	$PAGO^{\mathrm{pa}}$	$PAGO^{\mathrm{pa}}$	$PAGO^{\mathrm{pa}}$	$PAGO^{\mathrm{pa}}$	$PAGO^{\mathrm{pa}}$
c	−0.63	−2.78	−11.22	−3.50	−7.50	-15.63^{**}
	(8.08)	(8.42)	(7.60)	(8.69)	(8.34)	(7.43)
$PAGO^{\mathrm{prelim}}$	0.79^{***}	0.85^{***}	0.86^{***}	0.83^{***}	0.82^{***}	0.82^{***}
	(0.06)	(0.07)	(0.06)	(0.06)	(0.06)	(0.06)
$PEXP^{\mathrm{prelim}}$	0.21^{**}	0.18^{*}	0.19^{**}	0.22^{**}	0.24^{**}	0.26^{**}
	(0.09)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)
Dif. Age			-1.20^{***}			-1.19^{***}
			(0.30)			(0.28)
Dif. End Grade				6.07^{**}		2.45
				(2.85)		(3.02)
Dif. Income					0.36^{***}	0.33^{***}
					(0.11)	(0.10)
Wald1	7.34	8.59	3.11	9.24	5.47	5.40
p-value	< 0.001	< 0.001	0.028	< 0.001	0.001	0.001
R^2	0.74	0.75	0.77	0.76	0.76	0.78

(b) Effect via BUS1Y

	$PAGO^{\mathrm{np}}$	$PAGO^{\mathrm{pa}}$	$PAGO^{\mathrm{pa}}$	$PAGO^{\mathrm{pa}}$	$PAGO^{\mathrm{pa}}$	$PAGO^{\mathrm{pa}}$
c	19.15^{***}	12.92^{**}	5.48	14.39^{***}	12.35^{**}	5.53
	(5.96)	(5.50)	(4.78)	(4.85)	(4.78)	(4.23)
$PAGO^{\mathrm{prelim}}$	0.74^{***}	0.82^{***}	0.84^{***}	0.82^{***}	0.81^{***}	0.82^{***}
	(0.09)	(0.10)	(0.09)	(0.09)	(0.09)	(0.08)
$BUS1Y^{\mathrm{prelim}}$	0.11^{**}	0.10	0.10	0.10	0.10	0.10^{*}
	(0.05)	(0.07)	(0.06)	(0.06)	(0.06)	(0.06)
Dif. Age			-1.19^{***}			-1.17^{***}
			(0.28)			(0.26)
Dif. End Grade				5.28^{*}		1.72
				(2.83)		(2.97)
Dif. Income					0.33^{***}	0.30^{***}
					(0.11)	(0.10)
Wald1	7.69	9.10	2.07	9.22	5.13	3.23
p-value	< 0.001	< 0.001	0.106	< 0.001	0.002	0.024
R^2	0.74	0.75	0.77	0.75	0.76	0.78

This table shows the results of regressions of $PAGO_t^{\mathrm{np}}$ and $PAGO_t^{\mathrm{pa}}$ on a constant, $PAGO_t^{\mathrm{prelim}}$, the preliminary values of the forward-looking variables and control variables. The preliminary forward-looking variables *PEXP*, *BUS1Y* and *BUS5Y* are considered separately in panels (a-c) and jointly in panel (d). The preliminary variables are published during month t. $PAGO_t^{\mathrm{pa}}$ is based on the interviews taken after the announcement of the preliminary values, and is available from January 2000 onwards. To create the $PAGO_t^{\mathrm{np}}$ series, we augment the $PAGO_t^{\mathrm{pa}}$ series for the period from January 1991 to January 2000 based on the difference between the final and preliminary values for $PAGO_t$, using the average weights for the period after 2000. As control variables, we include the differences between the weighted averages of age, end grade and income between the post-announcement and preliminary sub samples. We report parameter estimates with standard errors in parentheses based on Newey and West (1987) with the Bartlett kernel and a bandwidth value of 12. The row "Wald1" gives the result of the Wald-test of the hypothesis that the intercept and the coefficients on $PAGO_t^{\mathrm{prelim}}$ and the forward-looking variables are equal to zero, one and zero, respectively, with the p-value based on an F-distribution given below. The row "Wald2" in panel (d) gives the result of the Wald-tests of the hypothesis that the coefficients on the forward-looking variables are equal to zero, with the p-value based on an F-distribution given below. The row "R^2" gives the adjusted R^2. Superscripts ***,** ,* indicate significance at the 1, 5 and 10% level. The results for $PAGO_t^{\mathrm{np}}$ and $PAGO_t^{\mathrm{pa}}$ are based on 288 and 180 observations.

Table 6: Test of the Herding Effect – *continued*

(c) Effect via BUS5Y

	$PAGO^{\mathrm{np}}$	$PAGO^{\mathrm{pa}}$	$PAGO^{\mathrm{pa}}$	$PAGO^{\mathrm{pa}}$	$PAGO^{\mathrm{pa}}$	$PAGO^{\mathrm{pa}}$
c	12.95***	9.28**	1.43	10.48**	7.89*	0.71
	(4.92)	(4.67)	(4.59)	(4.33)	(4.04)	(3.87)
$PAGO^{\mathrm{prelim}}$	0.81***	0.90***	0.90***	0.88***	0.87***	0.87***
	(0.07)	(0.07)	(0.06)	(0.07)	(0.07)	(0.06)
$BUS1Y5Y^{\mathrm{prelim}}$	0.10**	0.05	0.07	0.07	0.08	0.11
	(0.05)	(0.07)	(0.07)	(0.06)	(0.06)	(0.06)
Dif. Age			−1.20***			−1.19***
			(0.29)			(0.27)
Dif. End Grade				5.73**		2.27
				(2.90)		(3.05)
Dif. Income					0.34***	0.31***
					(0.11)	(0.10)
Wald1	6.66	7.96	1.81	7.89	4.94	2.91
p-value	< 0.001	< 0.001	0.147	< 0.001	0.003	0.036
R^2	0.74	0.75	0.76	0.75	0.76	0.78

(d) Effect via PEXP, BUS1Y and BUS5Y

	$PAGO^{\mathrm{np}}$	$PAGO^{\mathrm{pa}}$	$PAGO^{\mathrm{pa}}$	$PAGO^{\mathrm{pa}}$	$PAGO^{\mathrm{pa}}$	$PAGO^{\mathrm{pa}}$
c	9.51	1.75	−6.14	0.84	−2.66	−10.58
	(9.53)	(11.35)	(9.88)	(11.15)	(11.05)	(9.76)
$PAGO^{\mathrm{prelim}}$	0.71***	0.79***	0.80***	0.78***	0.77***	0.77***
	(0.09)	(0.09)	(0.08)	(0.09)	(0.09)	(0.08)
$PEXP^{\mathrm{prelim}}$	0.13	0.22*	0.22*	0.24*	0.25**	0.25**
	(0.09)	(0.13)	(0.13)	(0.13)	(0.13)	(0.12)
$BUS1Y^{\mathrm{prelim}}$	0.10	0.15	0.14	0.12	0.12	0.10
	(0.07)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)
$BUS5Y^{\mathrm{prelim}}$	−0.01	−0.19	−0.16	−0.15	−0.14	−0.10
	(0.08)	(0.13)	(0.14)	(0.12)	(0.13)	(0.13)
Dif. Age			−1.17***			−1.17***
			(0.29)			(0.28)
Dif. End Grade				5.25*		1.90
				(2.77)		(2.85)
Dif. Income					0.34***	0.32***
					(0.12)	(0.11)
Wald1	4.87	6.20	3.05	6.21	3.43	4.20
p-value	< 0.001	< 0.001	0.012	< 0.001	0.006	0.001
Wald2	2.38	1.85	2.07	2.00	2.31	2.74
p-value	0.070	0.141	0.106	0.116	0.078	0.045
R^2	0.74	0.75	0.77	0.76	0.77	0.78

See table note on previous page.

A Additional Data Analysis

A.1 Index of Consumer Sentiment Data

We show the evolution of the different ICS variables in Figure A.1 and investigate their time-series properties in Table A.1. The unit root tests all indicate that the ICS series is stationary. The (adjusted) Dickey-Fuller and Phillips-Perron tests reject the null-hypothesis of a unit root with p-values below 5%, and the KPSS-statistic is close to the 10% critical value. The results in panel (b) show that an AR(1)-model fits the data accurately. Higher order AR-terms and MA-terms do not improve the model.

[Figure A.1 about here.]

[Table A.1 about here.]

[Table A.1 (continued) about here.]

For the PAGO series, the evidence is less clear cut. The Dickey-Fuller and Phillips-Perron tests reject the hypothesis of a unit root, but the Adjusted Dickey-Fuller test does not reject. The KPSS-test does not reject stationarity at the 5% level. Apparently, the lag structure is more intricate. Our results in panels (c) indicate a strong MA(1)-term next to an AR(1) term close the one. Since the MA(1)-term is negative, the effect of shocks is reduced. We do not find evidence in favour of higher order ARMA-models.

Our analysis of the PEXP series shows results that are comparable to the PAGO findings. We find rejection of a unit root by the DF- and PP-tests, but not by the ADF test. The KPSS-test rejects stationarity at 5% but not a the 1% confidence level. Also for PEXP, an ARMA(1,1) model seems most suitable, though an ARMA(2,1) scores only slightly worse based on BIC. For both the PAGO and PEXP series we maintain the hypothesis of stationarity.

For the other four series, the hypothesis of a unit root is clearly rejected by the three tests, and the KPSS statistics do not reject the hypothesis of stationarity. All series show evidence of ARMA effects, with some variation over the exact specification. For BUS1Y, an AR(1)-model works well. For BUS5Y an ARMA(2,1)-specification performs slightly better than an ARMA(1,1). For DUR, we find an ARMA(1,1), and for BAGO an AR(2). We take these ARMA effects into account in our main analyses.

A.2 Explanatory Variables in the Peak-End Analysis

We provide an overview of the data that we use for the explanatory variables in Section 4 in Table A.2. Some further remarks

- LABI is based on a large set of government and corporate bonds. We transfer the discrete returns to log returns.
- HPIM is based on purchases only. HPIQ also includes appraisal data.
- The CPI series is reset on January 1988. We have compiled a new series with a single base date based on the relative changes reported in ALFRED.

[Table A.2 about here.]

A.3 Demographic variables in the CAB

Table A.3 gives an overview of the demographic variables that we evaluate as control variables for the herding analysis in Section 5. We transform the binary variables such that their average value gives the percentage of respondents that own a home (HOMEOWN), have stock market investments (INVEST), or are female (SEX). Marital status 2 (separated) does never occur in our sample period.

[Table A.3 about here.]

In each month, we calculate the weighted average of each non-categorical demographic variable, and the weighted frequency of each category of the categorical variables. We create subsamples for the respondents whose responses are included in the preliminary annoucements (prelim) and those whose interviews take place after the preliminary announcement (pa). The differences between the prelim- and pa-values are used as regressors in Section 5.

We test for the presence of a structural difference between the premlim- and pa-values. For the discrete and continuous variables, we use a linear panel model with time-fixed effects,

$$y_{it} = \mu_t + \delta d_{it} + \varepsilon_{it}, \quad \varepsilon_{it} \sim \mathrm{NID}(0, \sigma^2), \tag{A.1}$$

where y_{it} gives the value for respondent i in month t, $d_{it} = 1$ if the respondent is interviewed after the preliminary announcement and zero otherwise, and μ_t and δ are parameters. Our test for a structural difference between the prelim- and pa-values takes the form of a t-test of $\delta = 0$ versus $\delta \neq 0$. We estimate the parameters and conduct the test using weighted linear regression, with the weights as present in the CAB.

For the binary and categorical variables, we model the probability of the respondent belonging to category c out of C categories as

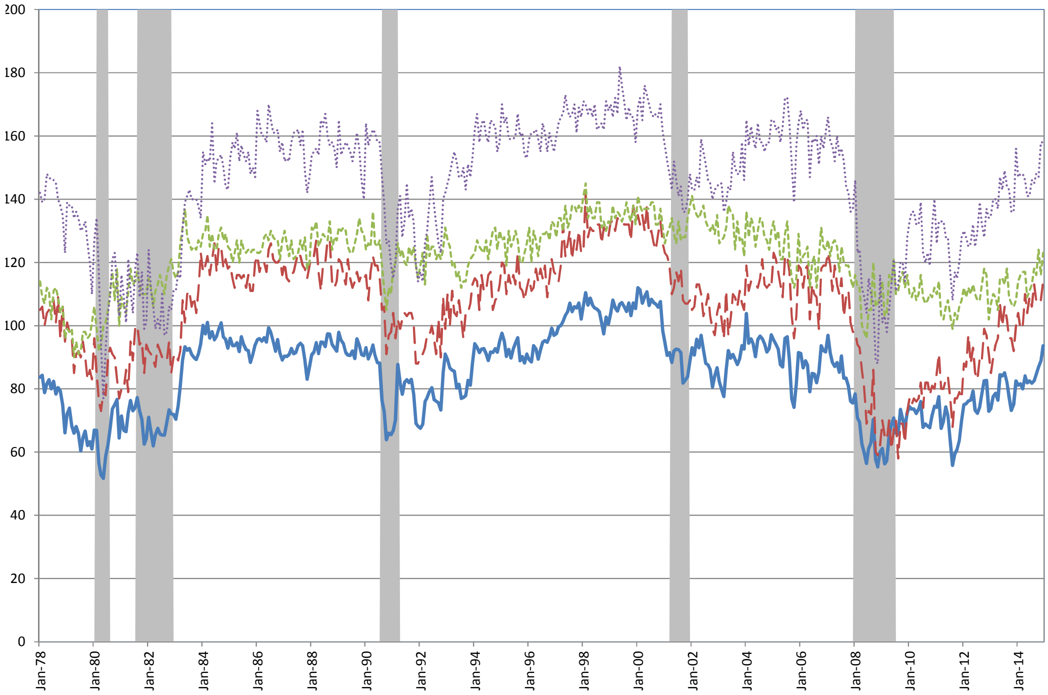
$$\Pr[y_{ict} = 1] = p_{ct} + \delta_c d_{it}, \tag{A.2}$$

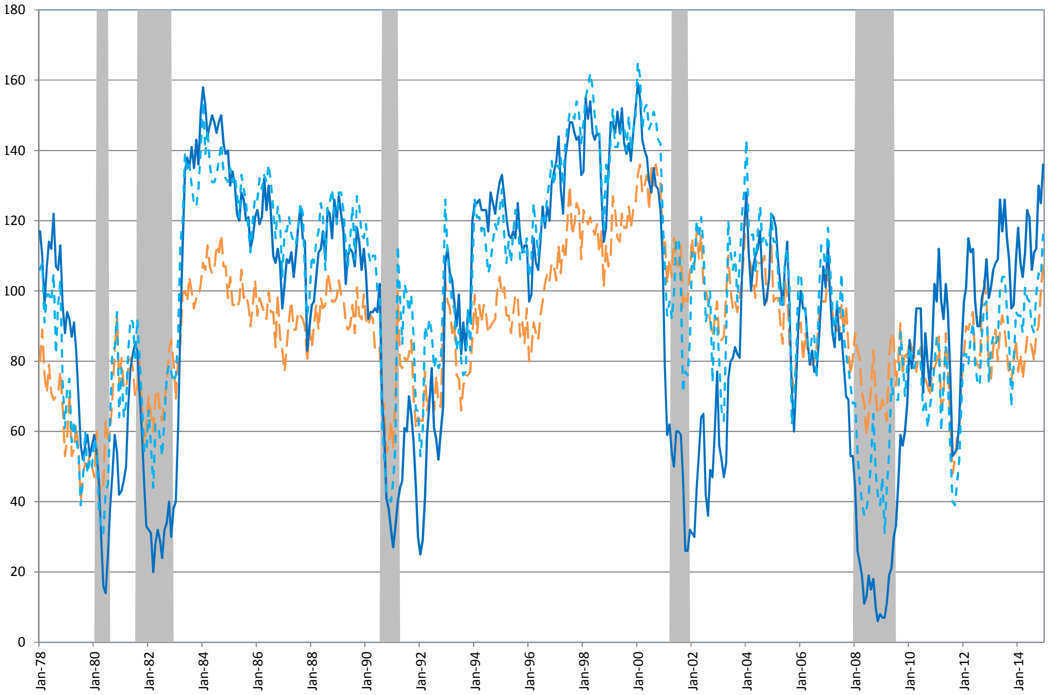
where $y_{ict} = 1$ if respondent i in month t belongs to category c, and zero otherwise. The parameters are restricted by $\sum_{c=1}^{C} p_{ct} = 1$ for each t and $\sum_{c=1}^{C} \delta_c = 0$. We estimated the parameters by weighted maximum likelihood, and test again $\delta = 0$ by a t-test.

Table A.4 presents summary statistics of the different demographic variables. We present the time-series averages and standard deviations of the prelim- and pa-values, and our test for structural differences. Pa-respondents are on average 5 years younger, and have received slightly less schooling. They are less likely to own a house (by 5.6%), though if they do the house is worth \$ 17,000 more. Their income is on average \$ 3,800 higher. They are less likely to invest (by 2.3%), and their portfolio is also worth less (by \$ 35,000). The average number of adults and children are higher, and they are more likely to be female. They are more likely to be married or partnered, or to have never married, but less likely to be widowed. Finally, pa-respondents are more likely to live in the West and less in North-Central. Most differences are significant, but this result is largely due to the size of the panel (mostly 180 months with around 500 respondents per month).

[Table A.4 about here.]

Figure A.1: Evolution of ICS variables





This figure shows the monthly values for ICS (blue, solid line), PAGO (red, long-dashed line), PEXP (green, short-dashed line) and DUR (purple, dotted line) in the top panel, and BUS1Y (light blue, short-dashed line), BUS5Y (orange, long-dashed line) and BAGO (blue, solid line) over the period January 1978 – December 2014. The grey areas indicate the NBER recession periods.

Table A.1: Time Series Properties of CAB series

(a) Unit Root Tests

	ICS	PAGO	PEXP	BUS	BUS5Y	DUR	BAGO
DF, p-value	0.019	0.002	< 0.0001	0.003	0.0002	0.002	0.074
ADF, lags	0	2	5	0	1	1	1
ADF, p-value	0.019	0.149	0.204	0.003	0.003	0.016	0.018
PP, p-value	0.038	0.023	0.0001	0.006	0.001	0.010	0.028
KPSS, statistic	0.348	0.394	0.470	0.322	0.415	0.336	0.130

(b) ARMA models for ICS

C	AR(1)	AR(2)	MA(1)	MA(2)	BIC
85.4	0.95		−0.003		5.6303
(4.04)	(0.02)		(0.05)		
85.4	0.95	0.003			5.6303
(4.04)	(0.04)	(0.04)			
85.4	0.95				5.6165
(4.02)	(0.02)				

(c) ARMA models for PAGO

C	AR(1)	AR(2)	MA(1)	MA(2)	BIC
106.2	1.27	−0.28	−0.73	0.11	6.3974
(7.68)	(1.67)	(1.63)	(1.67)	(0.77)	
106.2	1.03	−0.05	−0.50		6.3840
(7.62)	(0.10)	(0.09)	(0.09)		
106.2	0.98		−0.44	−0.02	6.3841
(7.59)	(0.01)		(0.04)	(0.04)	
106.1	0.60	0.35			6.3982
(5.78)	(0.04)	(0.04)			
106.2	0.98		−0.45		6.3709
(7.45)	(0.01)		(0.04)		
106.0	0.93				6.5154
(4.10)	(0.02)				

(d) ARMA models for PEXP

C	AR(1)	AR(2)	MA(1)	MA(2)	BIC
119.9	1.44	−0.45	−0.92	0.13	5.9759
(5.05)	(0.32)	(0.31)	(0.32)	(0.19)	
120.0	1.22	−0.24	−0.70		5.9642
(4.85)	(0.09)	(0.08)	(0.06)		
120.2	0.98		−0.47	−0.10	5.9684
(4.54)	(0.01)		(0.04)	(0.05)	
120.9	0.61	0.32			6.0001
(2.88)	(0.04)	(0.04)			
120.5	0.97		−0.49		5.9641
(4.00)	(0.01)		(0.04)		
121.1	0.89				6.0921
(2.11)	(0.02)				

This table shows the resuls of a time-series analysis for the CAB series. Panel (a) gives the results of the following unit root tests: Dickey-Fuller (DF), Adjusted Dickey Fuller (ADF) with automatic lag selection based on BIC, Phillips-Perron (PP) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS). The last two use the Bartlett kernel and Newey-West bandwidth. The p-values of the first three tests are reported, and the statistic of the KPSS test. Critical values for the KPSS test are 0.347, 0.463 and 0.739 at the 10, 5 and 1% confidence level. Panels (b-h) show the estimation results for various ARMA-models. Standard errors are reported in parenthesis. The column labeled "C" gives the unconditional average. The column labeled "BIC" gives the Bayesian Information Criterion.

Table A.1: Time Series Properties of CAB series – *continued*

(e) ARMA models for BUS

C	AR(1)	AR(2)	MA(1)	MA(2)	BIC
100.7	0.97	−0.04			7.6139
(7.66)	(0.05)	(0.04)			
100.7	0.93		0.05		7.6136
(7.60)	(0.02)		(0.05)		
100.7	0.93				7.6017
(7.92)	(0.02)				

(f) ARMA models for BUS5Y

C	AR(1)	AR(2)	MA(1)	MA(2)	BIC
89.6	1.26	−0.28	−0.52	−0.06	6.9583
(6.26)	(0.34)	(0.32)	(0.34)	(0.11)	
89.6	1.41	−0.43	−0.68		6.9452
(6.38)	(0.14)	(0.13)	(0.12)		
89.7	0.96		−0.23	−0.13	6.9459
(5.96)	(0.01)		(0.05)	(0.05)	
89.8	0.77	0.15			6.9554
(4.68)	(0.04)	(0.04)			
89.8	0.94		−0.23		6.9468
(5.16)	(0.02)		(0.04)		
89.7	0.91				6.9646
(3.95)	(0.02)				

(g) ARMA models for DUR

C	AR(1)	AR(2)	MA(1)	MA(2)	BIC
144.9	1.34	−0.35	−0.60	−0.01	6.8457
(8.12)	(0.35)	(0.34)	(0.36)	(0.12)	
144.9	1.36	−0.38	−0.63		6.8321
(8.13)	(0.14)	(0.13)	(0.12)		
144.9	0.97		−0.24	−0.11	6.8346
(7.70)	(0.01)		(0.04)	(0.05)	
144.8	0.77	0.17			6.8388
(6.23)	(0.04)	(0.04)			
144.9	0.96		−0.24		6.8306
(6.85)	(0.01)		(0.04)		
144.7	0.93				6.8551
(5.19)	(0.02)				

(h) ARMA models for BAGO

C	AR(1)	AR(2)	MA(1)	MA(2)	BIC
95.8	0.99	−0.04	0.15	0.10	7.4200
(10.57)	(0.49)	(0.47)	(0.49)	(0.10)	
95.9	1.28	−0.32	−0.13		7.4096
(10.64)	(0.24)	(0.23)	(0.25)		
95.9	0.94		0.20	0.11	7.4063
(10.62)	(0.02)		(0.05)	(0.05)	
96.0	1.15	−0.19			7.3972
(10.98)	(0.05)	(0.04)			
96.2	0.95		0.17		7.4020
(11.63)	(0.02)		(0.05)		
96.9	0.97				7.4204
(13.43)	(0.01)				

See table note on previous page.

Table A.2: Source and Description of Explanatory Variables in the Peak-End Analysis

(a) Financial Variables

Abbrev.	Source	ID	Freq.	Unit	First Obs.	Description
SP500	Bloomberg		M	Index	Jan-78	S&P500 index
LABI	Datastream	LHAGGBD(PRIR)	M	Percent	Jan-78	Barclays US Aggregate - price return
HPIQ	FRED	USSTHPI	Q	Index 1980:Q1=100	Jan-78	All-Transactions House Price Index for the US
UST3M	FRED	TB3MS	M	Percent	Jan-78	3-Month Treasury Bill: Secondary Market Rate
UST10Y	FRED	GS10	M	Percent	Jan-78	10-Year Treasury Constant Maturity Rate
NASDAQ	Bloomberg		M	Index, 5 Feb 1971 = 100	Jan-78	NASDAQ Composite Index
HPIM	FRED	HPIPONM226S	M	Index Jan 1991=100	Jan-92	Purchase Only House Price Index for the US

(b) Macro Variables

Abbrev.	Source	ID	Freq.	Unit	First Obs. ALFRED	First Obs. FRED	Description
CPI	(AL)FRED	CPIAUCSL	M	Index 1982-1984=100	Jan-78	Jan-78	Consumer Price Index for All Urban Consumers: All Items
GNP	(AL)FRED	GNP	Q	Billions of Dollars	Jan-78	Jan-78	Gross National Product
NFP	(AL)FRED	PAYEMS	M	Thousands of Persons	Jan-78	Jan-78	All Employees: Total Nonfarm Payrolls
UNEMP	(AL)FRED	UNRATE	M	Percent	Jan-78	Jan-78	Civilian Unemployment Rate
PCE	(AL)FRED	PCE	M	Billions of Dollars	Jan-81	Jan-78	Personal Consumption Expenditures
GDP	(AL)FRED	GDP	M	Billions of Dollars	Apr-93	Jan-78	Gross Domestic Product
IP	FRED	INDPRO	M	Index 2012=100	NA	Jan-78	Industrial Production Index
PCEND	(AL)FRED	PCEND	M	Billions of Dollars	Jan-81	Jan-78	Personal Consumption Expenditures: Nondurable Goods
PCEDG	(AL)FRED	PCEDG	M	Billions of Dollars	Jan-81	Jan-78	Personal Consumption Expenditures: Durable Goods
PCES	(AL)FRED	PCES	M	Billions of Dollars	Jan-81	Jan-78	Personal Consumption Expenditures: Services

This table gives for each variable used in the analyses of the peak and end rules in Section 4 the abbreviation that we use, the source, the ID in this source, the frequency (M for monthly, Q for Quarterly), the unit, the data of the first observation that we use in the analysis and a brief description. For the macro variables we use both vintage data from ALFRED and final data from FRED. ALFRED and FRED are available from the Federal Reserve Bank of St. Louis.

Table A.3: Demographics Codebook

Variable	Content	Type	Labels
AGE	Age of Respondent	Discrete	97: 97 or older
EGRADE	Highest Grade Completed	Discrete	
HOMEAMT	Market Value of Home	Continuous	$\times$ 1000
HOMEOWN	Own or Rent Home	Binary	1: Owns or is buying 2: Rent
INCOME	Total Income Previous Year	Continuous	x 1000
INVAMT	Current Investment Value Stock Market	Continuous	x 1000
INVEST	Have Stock Market Investments	Binary	1: Yes 5: No
MARRY	Marital Status	Categorical	1: Married/Partner 2: Seperated 3: Divorced 4: Widowed 5: Never married
NUMADT	Number of Adults (18+)	Discrete	
NUMKID	Number of Kids (<18)	Discrete	
REGION	Region of Residence	Categorical	1: West 2: North Central 3: Northeast 4: South
SEX	Sex of Respondent	Binary	1: Male 2: Female

This table gives an overview of the demographic variables that are collected in the CAB and we consider as control variables in Section 5. The columns “Variable” and “Content” give the abbreviation and definition that the CAB uses. In the column “Type” gives the type of the variables. The column label gives the coding for binary and categorical variables, and the transformation for the case of continuous variables. The information is taken from `https://data.sca.isr.umich.edu/sda-public/sca/Doc/sca.htm`.

Table A.4: Summary statistics of the demographic variables

(a) Non-categorical variables

		prelim		pa			
	obs.	average	std. dev.	average	std. dev.	δ	std. error
Age	180	52.87	3.06	47.93	3.09	-5.01^{***}	(0.13)
End Grade	180	14.07	0.27	13.90	0.34	-0.17^{***}	(0.02)
Homeamt (× 1,000)	111	253.70	27.12	270.49	36.95	16.93^{***}	(3.34)
Homeown (% owning)	180	77.42	4.89	72.81	5.56	-4.63^{***}	(0.33)
Income (× 1,000)	180	66.47	9.00	70.20	10.44	3.79^{***}	(0.54)
Invamt (× 1,000)	179	221.62	70.15	185.96	69.24	-35.57^{***}	(6.30)
Invest (% investing)	179	60.63	6.43	58.20	7.28	-2.34^{***}	(0.37)
Numadt	180	1.80	0.08	1.88	0.09	0.07^{***}	(0.01)
Numkid	180	0.59	0.09	0.77	0.14	0.19^{***}	(0.01)
Sex (% female)	180	54.20	2.57	54.65	4.46	0.49	(0.38)

(b) Marital status (% per category)

		prelim		pa			
	obs.	average	std. dev.	average	std. dev.	δ	std. error
Married / Partnered	180	59.34	3.09	61.20	4.99	1.94^{***}	(0.37)
Divorced	180	15.51	2.16	15.70	3.26	0.16	(0.28)
Widowed	180	11.84	1.91	7.30	2.24	-4.59^{***}	(0.21)
Never Married	180	13.31	2.80	15.80	3.95	2.49^{***}	(0.27)

(c) Region (% per category)

		prelim		pa			
	obs.	average	std. dev.	average	std. dev.	δ	std. error
North Central	180	25.41	1.99	22.97	3.63	-2.45^{***}	(0.32)
North East	180	18.89	1.73	18.67	3.16	-0.15	(0.30)
South	180	35.73	1.92	35.83	3.54	0.10	(0.37)
West	180	19.98	1.76	22.53	3.73	2.50^{***}	(0.31)

This table gives summary statistics of the monthly weighted averages of the non-categorical variables (panel a) and frequencies (panels b and c) of the categorical variables in the CAB. For each month, we calculate the weighted values using the weights that are assigned in the CAB. We split the sample according to those respondents whose responses are included in the preliminary announcement (prelim), and those respondents interviews after the preliminary announcement (pa). We report the time-series averages and standard deviations for both subsamples. We test whether for a structural differ between the prelim and pa groups and report the estimated difference in the column labeled "δ" with its standard error next to it. For the discrete and continuous variables, we estimate δ in the panel model of Equation (A.1) with weighted least squares. For the binary and categorical variables, we estimate δ in the panel model of Equation (A.2) with weighted maximum likelihood. We test $\delta = 0$ by a t-test and evaluate the test-statistic by a normal distribution. Superscripts ***,**,* indicate significance at the 1, 5 and 10% level.

B Additional Results

B.1 Additional results for the herding analysis

[Table B.1 about here.]

[Table B.1 (continued) about here.]

[Table B.2 about here.]

[Table B.2 (continued) about here.]

[Table B.3 about here.]

[Table B.3 (continued) about here.]

[Table B.4 about here.]

[Table B.5 about here.]

[Table B.5 (continued) about here.]

[Table B.6 about here.]

Table B.1: Test of the Herding Effect with Non-categorical Control Variables

(a) Effect via PEXP

	Age	Egrade	Homeamt	Homeown	Income	Invamt	Invest	Numadt	Numkid	Sex
c	−11.22	−3.50	−2.84	−2.69	−7.50	−2.84	−6.24	−5.53	−6.38	−3.43
	(7.60)	(8.69)	(8.07)	(8.30)	(8.34)	(8.07)	(8.13)	(7.50)	(8.09)	(8.31)
$PAGO^{\text{prelim}}$	0.86***	0.83***	0.83***	0.86***	0.82***	0.83***	0.82***	0.86***	0.86***	0.85***
	(0.06)	(0.06)	(0.07)	(0.07)	(0.06)	(0.07)	(0.08)	(0.07)	(0.07)	(0.07)
$PEXP^{\text{prelim}}$	0.19**	0.22**	0.21**	0.17	0.24**	0.21**	0.24**	0.19*	0.19*	0.19*
	(0.10)	(0.10)	(0.09)	(0.10)	(0.10)	(0.09)	(0.10)	(0.10)	(0.10)	(0.10)
Control var.	−1.20***	6.07**	−0.02	−0.15	0.36***	0.02*	0.15	15.82	9.51*	0.19
	(0.30)	(2.85)	(0.03)	(0.14)	(0.11)	(0.01)	(0.15)	(10.85)	(5.66)	(0.15)

(b) Effect via BUS1Y

	Age	Egrade	Homeamt	Homeown	Income	Invamt	Invest	Numadt	Numkid	Sex
c	5.48	14.39***	14.50**	11.75**	12.35**	14.61***	13.57**	10.53**	9.70*	12.79**
	(4.78)	(4.85)	(6.62)	(5.83)	(4.78)	(5.47)	(5.67)	(4.52)	(4.93)	(5.40)
$PAGO^{\text{prelim}}$	0.84***	0.82***	0.71***	0.83***	0.81***	0.81***	0.81***	0.83***	0.84***	0.82***
	(0.09)	(0.09)	(0.10)	(0.10)	(0.09)	(0.10)	(0.10)	(0.09)	(0.09)	(0.09)
$BUS1Y1Y^{\text{prelim}}$	0.10	0.10	0.19***	0.09	0.10	0.10	0.10	0.10	0.10	0.10
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.07)	(0.07)	(0.07)	(0.06)	(0.06)
control	−1.19***	5.28*	−0.01	−0.18	0.33***	0.02	0.08	16.22	9.25	0.18
	(0.28)	(2.83)	(0.03)	(0.13)	(0.11)	(0.01)	(0.14)	(10.55)	(5.89)	(0.15)

This table shows the results of regressions of $PAGO_t^{\text{pa}}$ on a constant, $PAGO_t^{\text{prelim}}$, preliminary values of forward-looking variables and different control variables. The preliminary forward-looking variables $PEXP$, $BUS1Y1Y$ and $BUS5Y$ are considered separately in panels (a-c) and jointly in panel (d). The preliminary variables are published by the CAB during month t. $PAGO_t^{\text{pa}}$ is based on the interviews taken after the announcement of the preliminary values, and is available from January 2000 onwards. Each column reports the estimation results for the inclusion of the control variable in the column heading into the regression. The control variables are constructed as the difference between the weighted averages of the prelim and post-announcement observations. See Table A.3 for an explanation of the control variables. We report parameter estimates with standard errors in parentheses based on Newey and West (1987) with a Bartlett kernel and bandwidth value of 12. Superscripts ***,**,* indicate significance at the 1, 5 and 10% level.

Table B.1: Test of the Herding Effect with Non-categorical Control Variables – *continued*

(c) Effect via BUSL

	Age	Egrade	Homeamt	Homeown	Income	Invamt	Invest	Numadt	Numkid	Sex
c	1.43	10.48**	10.55*	8.26*	7.89*	10.81**	9.38**	6.88**	6.01	9.06*
	(4.59)	(4.33)	(6.32)	(4.91)	(4.04)	(4.72)	(4.72)	(3.48)	(4.45)	(4.76)
$PAGO^{\text{prelim}}$	0.90***	0.88***	0.87***	0.91***	0.87***	0.88***	0.88***	0.91***	0.91***	0.90***
	(0.06)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.08)	(0.07)	(0.07)	(0.07)
$BUS5Y^{\text{prelim}}$	0.07	0.07	0.06	0.04	0.08	0.06	0.07	0.05	0.05	0.06
	(0.07)	(0.06)	(0.07)	(0.07)	(0.06)	(0.07)	(0.07)	(0.07)	(0.06)	(0.06)
control	−1.20***	5.73**	−0.02	−0.18	0.34***	0.02*	0.10	15.42	9.33	0.19
	(0.29)	(2.90)	(0.03)	(0.13)	(0.11)	(0.01)	(0.15)	(10.79)	(5.76)	(0.15)

(d) Effect via PEXP, BUS1Y and BUSL

	Age	Egrade	Homeamt	Homeown	Income	Invamt	Invest	Numadt	Numkid	Sex
c	−6.14	0.84	20.58	1.98	−2.66	1.47	−1.31	−0.92	−1.88	1.13
	(9.88)	(11.15)	(14.42)	(11.28)	(11.05)	(10.84)	(10.61)	(11.04)	(10.38)	(11.05)
$PAGO^{\text{prelim}}$	0.80***	0.78***	0.72***	0.80***	0.77***	0.77***	0.76***	0.80***	0.80***	0.79***
	(0.08)	(0.09)	(0.09)	(0.10)	(0.09)	(0.09)	(0.10)	(0.09)	(0.09)	(0.09)
$PEXP^{\text{prelim}}$	0.22*	0.24*	0.04	0.21	0.25**	0.25*	0.27**	0.23*	0.23*	0.23*
	(0.13)	(0.13)	(0.15)	(0.13)	(0.13)	(0.13)	(0.12)	(0.14)	(0.13)	(0.13)
$BUS1Y1Y^{\text{prelim}}$	0.14	0.12	0.30***	0.15	0.12	0.14	0.14	0.15	0.15	0.14
	(0.10)	(0.10)	(0.08)	(0.10)	(0.10)	(0.10)	(0.10)	(0.11)	(0.11)	(0.10)
$BUS5Y^{\text{prelim}}$	−0.16	−0.15	−0.24***	−0.19	−0.14	−0.18	−0.17	−0.19	−0.18	−0.18
	(0.14)	(0.12)	(0.09)	(0.13)	(0.13)	(0.13)	(0.13)	(0.14)	(0.13)	(0.13)
Control	−1.17***	5.25*	−0.02	−0.16	0.34***	0.02	0.10	16.78	9.33	0.18
	(0.29)	(2.77)	(0.03)	(0.14)	(0.12)	(0.01)	(0.15)	(10.75)	(5.86)	(0.14)

See table note on previous page.

Table B.2: Test of the Herding Effect with Categorical Control Variables

(a) Effect via PEXP

	Marital status				Region			
	Married	Divorced	Widowed	Never married	North Central	North East	South	West
c	−4.17	−3.06	−5.78	−3.08	−2.71	−2.57	−3.18	−2.81
	(7.96)	(8.24)	(7.85)	(8.57)	(8.49)	(7.98)	(8.68)	(8.53)
$PAGO^{\text{prelim}}$	0.85***	0.85***	0.86***	0.85***	0.85***	0.85***	0.85***	0.85***
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
$PEXP^{\text{prelim}}$	0.19*	0.18*	0.19*	0.18*	0.18*	0.18*	0.19*	0.18*
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)
Control	0.16	−0.33	−0.32	0.19	−0.02	0.16	−0.15	0.04
	(0.14)	(0.26)	(0.22)	(0.14)	(0.15)	(0.17)	(0.17)	(0.16)

(b) Effect via BUS1Y

	Marital status				Region			
	Married	Divorced	Widowed	Never married	North Central	North East	South	West
c	12.01**	12.44**	10.41**	12.47**	12.97**	12.71**	12.91**	13.31**
	(4.87)	(5.00)	(5.10)	(5.39)	(5.52)	(5.67)	(5.46)	(5.69)
$PAGO^{\text{prelim}}$	0.83***	0.83***	0.82***	0.82***	0.82***	0.83***	0.82***	0.80***
	(0.09)	(0.09)	(0.09)	(0.09)	(0.10)	(0.10)	(0.09)	(0.10)
$BUS1Y1Y^{\text{prelim}}$	0.09	0.09	0.10	0.10	0.10	0.09	0.10	0.11
	(0.07)	(0.07)	(0.06)	(0.06)	(0.07)	(0.07)	(0.07)	(0.07)
Control	0.14	−0.32	−0.36*	0.22*	−0.04	0.11	−0.17	0.13
	(0.14)	(0.26)	(0.22)	(0.13)	(0.15)	(0.18)	(0.18)	(0.16)

This table shows the results of regressions of $PAGO_t^{\text{pa}}$ on a constant, $PAGO_t^{\text{prelim}}$, preliminary values of forward-looking variables and different categorical control variables. See the note of Table B.1 for further explanations.

Table B.2: Test of the Herding Effect on *PAGO* with Categorical Control Variables – *continued*

(c) Effect via BUSL

	Marital status				Region			
	Married	Divorced	Widowed	Never married	North Central	North East	South	West
c	8.34^{**}	8.95^{**}	6.66	8.69^{*}	9.32^{**}	9.30^{**}	9.01^{*}	9.26^{*}
	(4.15)	(4.26)	(4.42)	(4.60)	(4.72)	(4.43)	(4.78)	(4.74)
$PAGO^{\text{prelim}}$	0.90^{***}	0.91^{***}	0.90^{***}	0.90^{***}	0.90^{***}	0.90^{***}	0.89^{***}	0.90^{***}
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.08)	(0.07)	(0.07)
$BUS5Y^{\text{prelim}}$	0.05	0.05	0.06	0.05	0.05	0.05	0.06	0.05
	(0.07)	(0.06)	(0.06)	(0.06)	(0.07)	(0.07)	(0.06)	(0.06)
control	0.15	−0.33	−0.32	0.20	−0.03	0.16	−0.16	0.05
	(0.14)	(0.26)	(0.22)	(0.14)	(0.15)	(0.19)	(0.17)	(0.17)

(d) Effect via PEXP, BUS1Y and BUSL

	Marital status				Region			
	Married	Divorced	Widowed	Never married	North Central	North East	South	West
c	0.22	1.05	−0.67	2.02	1.99	1.40	2.91	1.82
	(10.75)	(11.29)	(10.74)	(11.41)	(11.21)	(11.70)	(11.70)	(11.51)
$PAGO^{\text{prelim}}$	0.80^{***}	0.80^{***}	0.79^{***}	0.79^{***}	0.79^{***}	0.80^{***}	0.77^{***}	0.79^{***}
	(0.09)	(0.09)	(0.09)	(0.09)	(0.10)	(0.10)	(0.10)	(0.09)
$PEXP^{\text{prelim}}$	0.23^{*}	0.23^{*}	0.22	0.21	0.22^{*}	0.22^{*}	0.22	0.22^{*}
	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)
$BUS1Y1Y^{\text{prelim}}$	0.14	0.14	0.15	0.15	0.15	0.14	0.17	0.15
	(0.10)	(0.11)	(0.10)	(0.11)	(0.10)	(0.11)	(0.12)	(0.10)
$BUS5Y^{\text{prelim}}$	−0.18	−0.18	−0.18	−0.18	−0.19	−0.18	−0.19	−0.17
	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.14)	(0.12)
Control	0.14	−0.31	−0.34	0.21	−0.06	0.09	0.14	−0.14
	(0.14)	(0.26)	(0.21)	(0.13)	(0.13)	(0.17)	(0.15)	(0.16)

See table note on previous page.

Table B.3: Test of the Herding Effect on Changes

(a) Effect via changes in PEXP

	$\Delta PAGO^{\mathrm{np}}$	$\Delta PAGO^{\mathrm{pa}}$	$\Delta PAGO^{\mathrm{pa}}$	$\Delta PAGO^{\mathrm{pa}}$	$\Delta PAGO^{\mathrm{pa}}$	$\Delta PAGO^{\mathrm{pa}}$
c	2.72***	3.91***	−1.73	4.73***	2.86***	−2.30
	(0.58)	(0.71)	(1.52)	(0.95)	(0.73)	(1.76)
$\Delta PAGO^{\mathrm{prelim}}$	0.49***	0.52***	0.55***	0.52***	0.54***	0.57***
	(0.10)	(0.14)	(0.14)	(0.14)	(0.14)	(0.13)
$\Delta PEXP^{\mathrm{prelim}}$	0.17	0.30**	0.28*	0.28**	0.30**	0.27*
	(0.11)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)
Dif. Age			−1.14***			−1.13***
			(0.29)			(0.28)
Dif. End Grade				5.05*		1.98
				(2.62)		(2.72)
Dif. Income					0.29**	0.26**
					(0.12)	(0.11)
Wald1	16.60	13.75	4.74	13.91	7.81	4.79
p-value	< 0.001	< 0.001	0.003	< 0.001	< 0.001	0.003
R^2	0.13	0.17	0.22	0.18	0.20	0.25

(b) Effect via changes in BUS1Y

	$\Delta PAGO^{\mathrm{np}}$	$\Delta PAGO^{\mathrm{pa}}$	$\Delta PAGO^{\mathrm{pa}}$	$\Delta PAGO^{\mathrm{pa}}$	$\Delta PAGO^{\mathrm{pa}}$	$\Delta PAGO^{\mathrm{pa}}$
c	2.53***	3.45***	−2.28	4.36***	2.39***	−2.74
	(0.56)	(0.74)	(1.51)	(1.02)	(0.74)	(1.77)
$\Delta PAGO^{\mathrm{prelim}}$	0.52***	0.63***	0.66***	0.63***	0.65***	0.68***
	(0.10)	(0.14)	(0.13)	(0.13)	(0.13)	(0.12)
$\Delta BUS1Y^{\mathrm{prelim}}$	0.04	−0.01	−0.02	−0.03	−0.01	−0.03
	(0.05)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
Dif. Age			−1.17***			−1.15***
			(0.29)			(0.28)
Dif. End Grade				5.46**		2.42
				(2.73)		(2.85)
Dif. Income					0.29**	0.25**
					(0.12)	(0.12)
Wald1	16.95	11.27	4.67	11.66	6.24	4.63
p-value	< 0.001	< 0.001	0.004	< 0.001	< 0.001	0.004
R^2	0.13	0.15	0.20	0.16	0.18	0.24

This table shows the results of regressions of changes in $PAGO_t^{\mathrm{np}}$ and $PAGO_t^{\mathrm{pa}}$ on a constant, changes in $PAGO_t^{\mathrm{prelim}}$, and changes in the preliminary values of the forward-looking variables and control variables. The Δ-operator gives the difference of a variable with respect to the final value of that variable in the previous period. The forward-looking variables *PEXP*, *BUS1Y* and *BUS5Y* are considered separately in panels (a-c) and jointly in panel (d). We report parameter estimates with standard errors in parentheses based on Newey and West (1987) with the Bartlett kernel and a bandwidth value of 12. The results for $\Delta PAGO_t^{\mathrm{np}}$ and $\Delta PAGO_t^{\mathrm{pa}}$ are based on 288 and 180 observations. See Table 6 for further explanation.

Table B.3: Test of the Herding Effect on Changes – *continued*

(c) Effect via changes in BUS5Y

	$\Delta PAGO^{\mathrm{np}}$	$\Delta PAGO^{\mathrm{pa}}$	$\Delta PAGO^{\mathrm{pa}}$	$\Delta PAGO^{\mathrm{pa}}$	$\Delta PAGO^{\mathrm{pa}}$	$\Delta PAGO^{\mathrm{pa}}$
c	2.52^{***}	3.46^{***}	-2.24	4.34^{***}	2.40^{***}	-2.73
	(0.57)	(0.74)	(1.56)	(1.00)	(0.74)	(1.80)
$\Delta PAGO^{\mathrm{prelim}}$	0.52^{***}	0.64^{***}	0.65^{***}	0.62^{***}	0.65^{***}	0.66^{***}
	(0.10)	(0.13)	(0.13)	(0.13)	(0.13)	(0.12)
$\Delta BUS5Y^{\mathrm{prelim}}$	0.04	-0.03	-0.02	-0.02	-0.02	0.00
	(0.07)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)
Dif. Age			-1.16^{***}			-1.15^{***}
			(0.30)			(0.28)
Dif. End Grade				5.30^{**}		2.26
				(2.57)		(2.69)
Dif. Income					0.29^{**}	0.25^{**}
					(0.12)	(0.12)
Wald1	15.82	10.46	4.77	10.63	6.18	2.91
p-value	< 0.001	< 0.001	0.003	< 0.001	< 0.001	0.036
R^2	0.13	0.15	0.20	0.16	0.18	0.24

(d) Effect via changes in PEXP, BUS1Y and BUS5Y

	$\Delta PAGO^{\mathrm{np}}$	$\Delta PAGO^{\mathrm{pa}}$	$\Delta PAGO^{\mathrm{pa}}$	$\Delta PAGO^{\mathrm{pa}}$	$\Delta PAGO^{\mathrm{pa}}$	$\Delta PAGO^{\mathrm{pa}}$
c	2.70^{***}	4.02^{***}	-1.65	4.86^{***}	2.96^{***}	-2.19
	(0.59)	(0.72)	(1.57)	(1.00)	(0.74)	(1.80)
$\Delta PAGO^{\mathrm{prelim}}$	0.48^{***}	0.55^{***}	0.58^{***}	0.55^{***}	0.57^{***}	0.60^{***}
	(0.10)	(0.14)	(0.14)	(0.14)	(0.14)	(0.13)
$\Delta PEXP^{\mathrm{prelim}}$	0.16	0.36^{***}	0.35^{***}	0.35^{***}	0.36^{***}	0.34^{**}
	(0.11)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)
$\Delta BUS1Y^{\mathrm{prelim}}$	0.02	-0.03	-0.06	-0.08	-0.05	-0.09
	(0.07)	(0.10)	(0.10)	(0.10)	(0.09)	(0.09)
$\Delta BUS5Y^{\mathrm{prelim}}$	0.01	-0.08	-0.04	-0.03	-0.05	0.01
	(0.10)	(0.14)	(0.15)	(0.14)	(0.14)	(0.14)
Dif. Age			-1.15^{***}			-1.14^{***}
			(0.30)			(0.29)
Dif. End Grade				5.28^{*}		2.39
				(2.79)		(2.71)
Dif. Income					0.28^{**}	0.25^{**}
					(0.12)	(0.11)
Wald1	10.12	8.91	4.36	8.69	5.17	4.43
p-value	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
Wald2	0.75	3.53	3.19	3.91	3.40	3.33
p-value	0.521	0.016	0.025	0.010	0.019	0.021
R^2	0.13	0.16	0.22	0.18	0.19	0.25

See table note on previous page.

Table B.4: Estimates results for the VAR models of PAGO in combination with one or all of the forward-looking variables

(a) Sample period: Jan-1991 to Dec-2014

	$PAGO_t^{\text{final}}$	$PEXP_t^{\text{final}}$	$PAGO_t^{\text{final}}$	$BUS1Y1Y_t^{\text{final}}$	$PAGO_t^{\text{final}}$	$BUS5Y_t^{\text{final}}$	$PAGO_t^{\text{final}}$	$PEXP_t^{\text{final}}$	$BUS1Y1Y_t^{\text{final}}$	$BUS5Y_t^{\text{final}}$
ψ	−2.67	21.99***	12.50***	0.97	5.98***	6.24**	11.69**	28.96***	−6.79	−1.13
	(5.01)	(3.93)	(2.42)	(4.26)	(2.26)	(2.80)	(5.78)	(4.61)	(10.18)	(7.27)
$PAGO_{t-1}^{\text{final}}$	0.87***	0.09***	0.77***	0.13**	0.86***	0.11***	0.77***	0.04	0.11	0.03
	(0.04)	(0.03)	(0.04)	(0.07)	(0.03)	(0.04)	(0.04)	(0.03)	(0.07)	(0.05)
$PEXP_{t-1}^{\text{final}}$	0.13**	0.74***					0.02	0.65***	0.11	0.15*
	(0.06)	(0.05)					(0.07)	(0.05)	(0.12)	(0.09)
$BUS1Y1Y_{t-1}^{\text{final}}$			0.12***	0.85***			0.13***	0.03	0.85***	0.06
			(0.02)	(0.04)			(0.03)	(0.03)	(0.06)	(0.04)
$BUS5Y_{t-1}^{\text{final}}$					0.10***	0.81***	−0.03	0.07*	−0.02	0.71***
					(0.03)	(0.04)	(0.05)	(0.04)	(0.08)	(0.06)
R^2	0.87	0.77	0.88	0.86	0.87	0.81	0.88	0.77	0.86	0.81

(b) Sample period: Jan-2000 to Dec-2014

	$PAGO_t^{\text{final}}$	$PEXP_t^{\text{final}}$	$PAGO_t^{\text{final}}$	$BUS1Y1Y_t^{\text{final}}$	$PAGO_t^{\text{final}}$	$BUS5Y_t^{\text{final}}$	$PAGO_t^{\text{final}}$	$PEXP_t^{\text{final}}$	$BUS1Y1Y_t^{\text{final}}$	$BUS5Y_t^{\text{final}}$
ψ	1.49	18.30***	10.03***	6.65	5.36*	8.55**	11.50*	24.89***	3.67	2.15
	(5.78)	(4.70)	(2.72)	(4.74)	(2.78)	(3.34)	(6.49)	(5.33)	(11.30)	(7.86)
$PAGO_{t-1}^{\text{final}}$	0.89***	0.06*	0.80***	0.05	0.86***	0.07	0.80***	0.02	0.04	0.00
	(0.04)	(0.03)	(0.04)	(0.08)	(0.04)	(0.05)	(0.05)	(0.04)	(0.08)	(0.06)
$PEXP_{t-1}^{\text{final}}$	0.08	0.80***					0.01	0.67***	0.01	0.17
	(0.07)	(0.06)					(0.09)	(0.07)	(0.15)	(0.10)
$BUS1Y1Y_{t-1}^{\text{final}}$			0.11***	0.87***			0.14***	−0.01	0.83***	0.11*
			(0.03)	(0.05)			(0.05)	(0.04)	(0.08)	(0.06)
$BUS5Y_{t-1}^{\text{final}}$					0.09**	0.83***	−0.06	0.14**	0.08	0.65***
					(0.04)	(0.05)	(0.08)	(0.06)	(0.13)	(0.09)
R^2	0.87	0.77	0.88	0.83	0.88	0.80	0.88	0.78	0.83	0.80

This table gives the estimation results of the VAR models of order 1 that are formed by PAGO and one or all of the three forward-looking variables PEX, BUS1Y and BUSL. For all variables we use the final-series. The coefficients in the row ψ correspond with the intercept terms. We report parameter estimates with standard errors in parentheses. The row "R^2" gives the adjusted R^2. Superscripts ***,**,* indicate significant difference from zero at the 1, 5 and 10% level.

Table B.5: Estimation results for the predictive models for the forward-looking variables

(a) PEXP as dependent variable

	$PEXP^{\mathrm{np}}$	$PEXP^{\mathrm{pa}}$	$PEXP^{\mathrm{pa}}$	$PEXP^{\mathrm{np}}$	$PEXP^{\mathrm{pa}}$	$PEXP^{\mathrm{pa}}$
c	41.69***	30.60***	27.41***	50.04***	31.85***	28.75***
	(5.17)	(5.34)	(5.54)	(5.77)	(6.35)	(6.47)
$PEXP^{\mathrm{prelim}}$	0.62***	0.78***	0.77***	0.46***	0.76***	0.75***
	(0.06)	(0.07)	(0.07)	(0.07)	(0.08)	(0.08)
$BUS1Y1Y^{\mathrm{prelim}}$				−0.01	0.00	0.00
				(0.04)	(0.05)	(0.05)
$BUS5Y^{\mathrm{prelim}}$				0.23***	0.03	0.03
				(0.05)	(0.07)	(0.07)
$PAGO^{\mathrm{prelim}}$	0.09**	0.02	0.03	−0.01	0.01	0.03
	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)
Dif. Age			−0.60***			−0.61***
			(0.21)			(0.21)
Dif. End Grade			−0.57			−0.50
			(1.80)			(1.83)
Dif. Income			−0.07			−0.07
			(0.07)			(0.08)
R^2	0.56	0.67	0.69	0.61	0.67	0.69

(b) BUS1Y as dependent variable

	$BUS1Y1Y^{\mathrm{np}}$	$BUS1Y1Y^{\mathrm{pa}}$	$BUS1Y1Y^{\mathrm{pa}}$	$BUS1Y1Y^{\mathrm{np}}$	$BUS1Y1Y^{\mathrm{pa}}$	$BUS1Y1Y^{\mathrm{pa}}$
c	12.28***	18.98***	14.57**	17.88*	23.29**	18.69
	(4.36)	(5.06)	(5.74)	(9.68)	(11.43)	(11.85)
$PEXP^{\mathrm{prelim}}$				−0.07	−0.01	−0.01
				(0.11)	(0.15)	(0.15)
$BUS1Y1Y^{\mathrm{prelim}}$	0.88***	0.92***	0.93***	0.90***	0.98***	0.98***
	(0.04)	(0.06)	(0.06)	(0.06)	(0.08)	(0.08)
$BUS5Y^{\mathrm{prelim}}$				−0.01	−0.10	−0.10
				(0.08)	(0.13)	(0.13)
$PAGO^{\mathrm{prelim}}$	0.01	−0.09	−0.09	0.03	−0.08	−0.08
	(0.07)	(0.08)	(0.08)	(0.07)	(0.09)	(0.09)
Dif. Age			−0.50			−0.48
			(0.39)			(0.39)
Dif. End Grade			−3.53			−4.03
			(3.29)			(3.35)
Dif. Income			0.17			0.16
			(0.14)			(0.14)
R^2	0.85	0.80	0.81	0.84	0.80	0.81

This table shows the results of regressions of the forward-looking variables PEXP, BUS1Y and BUSL on a constant, their preliminary values, $PAGO_t^{\mathrm{prelim}}$ and control variables. We use both the non-prelim (np) and the post-announcement series. The preliminary variables are published by the CAB during month t. The pa-values are based on the interviews taken after the announcement of the preliminary values, and is available from January 2000 onwards. To create the np series, we augment the pa-series for the period from January 1991 to January 2000 based on the difference between the final and preliminary values, using the average weights for the period after 2000. As control variables, we include the differences between the weighted averages of age, end grade and income between the post-announcement and preliminary sub samples. We report parameter estimates with standard errors in parentheses. The row "R^2" gives the adjusted R^2. Superscripts ***,**,* indicate significance at the 1, 5 and 10% level. The results for np and pa-series are based on 288 and 180 observations.

Table B.5: Estimates for the predictive model for the forward-looking variables – *continued*

(c) BUSL as dependent variable

	$BUS5Y^{\mathrm{np}}$	$BUS5Y^{\mathrm{pa}}$	$BUS5Y^{\mathrm{pa}}$	$BUS5Y^{\mathrm{np}}$	$BUS5Y^{\mathrm{pa}}$	$BUS5Y^{\mathrm{pa}}$
c	0.68	−3.00	−5.53	−13.54	−20.81*	−24.43*
	(4.19)	(5.33)	(6.15)	(10.14)	(11.96)	(12.47)
$PEXP^{\mathrm{prelim}}$				0.21*	0.39**	0.40**
				(0.12)	(0.16)	(0.16)
$BUS1Y1Y^{\mathrm{prelim}}$				0.00	0.16*	0.14
				(0.06)	(0.09)	(0.09)
$BUS5Y^{\mathrm{prelim}}$	0.79***	0.82***	0.84***	0.74***	0.51***	0.54***
	(0.06)	(0.08)	(0.08)	(0.08)	(0.13)	(0.14)
$PAGO^{\mathrm{prelim}}$	0.20***	0.21***	0.20**	0.13*	0.07	0.07
	(0.06)	(0.08)	(0.08)	(0.08)	(0.09)	(0.09)
Dif. Age			−0.40			−0.36
			(0.42)			(0.41)
Dif. End Grade			1.57			1.10
			(3.56)			(3.52)
Dif. Income			0.07			0.08
			(0.15)			(0.15)
R^2	0.68	0.67	0.68	0.68	0.68	0.69

See table note on previous page.

Table B.6: Estimates for predictive models for the prelim values of the ICS variables

	(a) Sample Period: Jan-1991 to Dec-2014				(b) Sample Period: Jan-2000 to Dec-2014			
	$PAGO_t^{\text{prelim}}$	$PEXP_t^{\text{prelim}}$	$BUS1Y1Y_t^{\text{prelim}}$	$BUS5Y_t^{\text{prelim}}$	$PAGO_t^{\text{prelim}}$	$PEXP_t^{\text{prelim}}$	$BUS1Y1Y_t^{\text{prelim}}$	$BUS5Y_t^{\text{prelim}}$
Intercept	8.60	22.00***	−11.85	−7.83	7.30	17.46***	−2.89	−5.69
	(6.21)	(5.05)	(10.29)	(7.88)	(6.80)	(5.49)	(11.21)	(8.46)
$PAGO_{t-1}^{\text{final}}$	0.78***	0.05	0.17**	0.09*	0.82***	0.03	0.10	0.07
	(0.04)	(0.04)	(0.07)	(0.06)	(0.05)	(0.04)	(0.08)	(0.06)
$PEXP_{t-1}^{\text{final}}$	0.03	0.72***	0.07	0.16*	0.02	0.72***	−0.02	0.18
	(0.07)	(0.06)	(0.12)	(0.09)	(0.09)	(0.07)	(0.15)	(0.11)
$BUS1Y1Y_{t-1}^{\text{final}}$	0.13***	0.05*	0.82***	0.01	0.12**	0.00	0.81***	0.03
	(0.03)	(0.03)	(0.06)	(0.04)	(0.05)	(0.04)	(0.08)	(0.06)
$BUS5Y_{t-1}^{\text{final}}$	−0.02	0.01	0.03	0.75***	−0.04	0.13**	0.14	0.73***
	(0.05)	(0.04)	(0.08)	(0.06)	(0.08)	(0.06)	(0.13)	(0.10)
R^2	0.87	0.76	0.86	0.79	0.87	0.79	0.84	0.79
	Covariances				Covariances			
$PAGO_t^{\text{prelim}}$	43.37	12.67	23.72	13.88	43.12	15.25	31.13	19.81
$PEXP_t^{\text{prelim}}$	12.67	28.72	21.34	12.70	15.25	28.16	28.77	20.92
$BUS1Y1Y_t^{\text{prelim}}$	23.72	21.34	119.09	62.06	31.13	28.77	117.42	64.19
$BUS5Y_t^{\text{prelim}}$	13.88	12.70	62.06	69.85	19.81	20.92	64.19	66.86

This table shows the results of regressions of the prelim values of the ICS variables PAGO, PEXP, BUS1Y and BUSL on their final values in the previous period. We report parameter estimates with standard errors in parentheses. The row "R^2" gives the adjusted R^2. Superscripts ***,**,* indicate significance at the 1, 5 and 10% level. Below "Covariances" we report the variance-covariance matrix of the errors terms. We consider sample periods Jan-1991 to Dec-2014 (panel a) and Jan-2001 to Dec-2014 (panel b).