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Cognitive Biases and Consumer Sentiment*

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Abstract

We investigate whether two heuristics, the peak-end rule and herding, lead to cognitive biases in the index of consumer sentiment published by the University of Michigan. Both affect respondents' assessment of changes in their financial position over the past year. Consistent with the peak-end rule, respondents rely more on extreme detrimental monthly changes during the year than to changes over the whole year. We rule out that these extremes proxy for risk. The evidence for irrational herding consists in a too strong relationship from expectations about the future of respondents interviewed in a first round to assessments of the past by respondents interviewed in a second round. Both results show that cognitive biases can be found in a key macro variable and outside more controlled environments. They also indicate that the behavioral component of the sentiment index may offer another explanation for its relevance, next to news or animal spirits.

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

JEL classification: E71, E32, G41

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1 Introduction

Indexes that measure consumer sentiment are widely used in the construction of leading economic indicators, and for predictions in general. For example, the US Conference Board uses its own sentiment index in the construction of its leading economic indicator. However, the nature of their predictive ability is not yet fully understood. Carroll et al. (1994); Ludvigson (2004) show that they predict consumption, but that this effect cannot be fully explained by their predictive power for consumers' income or wealth. Compared to these and other objectively measured macroeconomic variables, indexes of consumer sentiment contain a subjective component, because they measure how consumers perceive the current economic situation and its outlook. Their added value may stem from reflecting consumers' perceptions, which can systemically deviate from objective assessments of the economy because consumers may be subject to cognitive biases in forming their perceptions.

Indexes of consumer sentiment may exhibit biases because of the way they are constructed. They are typically based on surveys among randomly picked households. The University of Michigan constructs its Index of Consumer Sentiment (ICS), which we analyze in this research, each month based on 500 interviews by telephone. The respondents answer five questions about the changes in their 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. This design forces respondents to make judgments on the spot.

To examine how the telephone survey can lead to biases in the answers, we use the research framework 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 judgment that are spontaneous, fast, automatic, effortless, associative and often emotionally charged. They are also governed by habit and therefore difficult to modify. To the contrary, judgments in system 2 are slower, serial, effortful, and deliberately controlled; they are also relatively flexible and potentially rule-governed.

In our research, we compare system 1 with system 2 judgments. Because respondents have to give answers on the spot, they may be inclined to take the heuristic approach of system 1 instead of making a more demanding macroeconomic or financial analysis that

corresponds with system 2. In particular, we focus on the survey question that asks how the financial position of a respondent has changed over the past year. Because this question is about the past we can determine which variables should be relevant in the rational analysis of system 2, and compare their explanatory power to variables that show up in system 1. For the questions that are related to respondents' expectations about the future, it is much harder or even impossible to specify which variables or relationships belong to system 1 or 2.

We investigate two heuristics that respondents can use in system 1 and which may lead to cognitive biases in the ICS, being the peak-end rule and herding. The number of cognitive biases that have been reported is large[1], but not all of them are relevant, or can be examined based on the available information. As we will explain, we focus on these two heuristics, because we can construct the relationship that should follow from either of these two biases, and the one we should observe in the unbiased system 2.

The peak-end rule states that when judging the sum of a sequence, agents base it on the most extreme and most recent observation in it (Varey and Kahneman, 1992; Fredrickson and Kahneman, 1993; Kahneman et al., 1993). If respondents use this rule to assess past changes in their financial position, past extreme and recent realizations of key financial and macroeconomic variables should explain the aggregate answer to this question. If respondents use system 2, it should rather be the yearly changes. As explanatory variables, we analyze financial variables like returns on the stock, bond and housing markets, and changes in interest rates, and macro variables related to inflation, economic growth and unemployment. We compare the explanatory power of the sum of monthly changes in these variables with transformations of these sequences based on the peak-end rule.

Our results provide evidence in favor of the peak part of the peak-end rule. Detrimental extremes experienced during the last year are better able to explain respondents aggregate assessment of changes in their financial position than changes over the whole year. In linear regressions, the effect of yearly changes becomes smaller and mostly disappears when we include detrimental extremes. These results remain present when we include the past volatility of the explanatory variables, which shows that the explanatory power of extremes is not caused by respondents' being risk-averse.

We do not find evidence for the end part of the peak-end rule. Though the most recent observation is a reasonable proxy for the yearly change, it has no effect when included jointly

[1]The wikipedia-page `https://en.wikipedia.org/wiki/List_of_cognitive_biases` lists around 200.

with the yearly change in a regression. A potential reason for the absence of the end-part may be the design of our analysis. We do not actually know whether respondents have observed the sequence to which we apply the peak-end rule. Contrary to extremes, most recent realizations do not automatically receive media attention, making it less likely that agents are aware of them.

The second heuristic that we investigate is herding. We examine how the beliefs from respondents that are interviewed earlier in a month influence subsequent respondents. Herding belongs to system 2 and is rational, if agents update their beliefs based on the beliefs of others that have better information. However, if agents put too much weight on the information of others, herding belongs to system 1 and can be considered irrational. To design our analysis of herding, we use the preliminary announcement that the University of Michigan publishes each month based on the first 300-330 surveys that have been conducted. This announcement reports the preliminary aggregate value of the index and the aggregate answer to the five constituting questions. If the rational herding of system 2 is present, the preliminary aggregate assessment of the past changes should perfectly predict the aggregate assessment of the respondents that are interviewed after the preliminary announcement. The preliminary aggregate answers to the questions that relate to future expectations should not add further predictive power, because they relate to the future and not to the past. However, if we find that both the preliminary assessment of the past and expectations about the future predict the post-announcement assessment of the past, this finding indicates that the post-announcement respondents pay too much attention to the sentiment of others.

Our results show the presence of irrational herding. In a regression of the aggregate post-announcement assessment of past financial changes, both the preliminary assessment of past financial changes and the preliminary expectation of future financial changes are significant. We reject the hypotheses corresponding with herding in system 2 that the effect of expected financial changes is absent, and that assessment of past financial changes constitute a perfect predictor (i.e., with a coefficient equal to 1). We also find effects from the preliminary expectation about future business conditions, albeit weaker. The effects become stronger when we account for systematic differences in the sample composition between the subsample of respondents interviewed before and after the announcement. 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.

The main contribution of our research consists in presenting evidence that cognitive biases can be found outside more controlled and laboratory settings. 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 rule is vast (see surveys by Fredrickson, 2000; Kahneman, 2000). Consistent with this evidence (see also 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.

Evidence of herding is largely based on laboratory experiments (see Hommes, 2011, for a survey), because it is generally difficult to account for agents' information sets. Moreover, research into herding focuses on inferences based on the observable actions of agents or resulting pricing information (see, for example, the classical model in Banerjee, 1992 or the more general discussion in Chamley, 2004). The preliminary publication of the survey results creates a direct connection between beliefs and leads to herding in the style of Baddeley et al. (2004). The unique feature of the Michigan survey asking respondents to assess past change in their financial position creates an opportunity to test for irrational herding.

We also contribute to the debate about the meaning of indexes of consumer sentiment next to other macroeconomic variables. Though many authors show that they are useful for forecasting[2], there is less consensus on their added value and the causes of it. Fuhrer (1993) claims that they are only relevant because they predicts other macrovariables and are more timely available. To the contrary, Carroll et al. (1994); Ludvigson (2004) show that the predictive power of the sentiment index does not simply come from predicting household income or wealth, and Souleles (2004) shows this for other macro variables. Barsky and Sims (2012) argue that the predictive power is due to news and not because of "animal spirits". Our finding of the presence of cognitive biases gives another explanation for their information content. If consumers process information in a biased way, the effect of these biases will contribute to the added value of indexes of consumer sentiment in comparison with other macro variables. The setting of on-the-sport answers in a telephone survey may actually

[2]The predictive value of indexes of consumer sentiment has been investigated mostly for consumer spending, in the U.S. (Fuhrer, 1988, 1993; Carroll et al., 1994; Bram and Ludvigson, 1998; Ludvigson, 2004; Souleles, 2004), the UK (Acemoglu and Scott, 1994; Easaw et al., 2005) and the Euro area (Dees and Brinca, 2013). There is also evidence that they are useful for more general economic predictions (Taylor and McNabb, 2007) and predictions in financial markets (Baker and Wurgler, 2006; Lemmon and Portniaguina, 2006).

be representative of the heuristic approach with which consumers generally assess the economy. In this explanation, the indexes do neither show news that is not yet present in other macro variables (Cochrane, 1994), nor do they capture sudden "animal spirits/taste-shocks" (Blanchard, 1993). Instead, they show how cognitive biases affect consumers' forming of judgments about the economy in a systematic way.

The remainder of this article is structured as follows. In section two we present the theoretical framework of our research. In section three we discuss the data. In section four we investigate the peak-end rule, and we turn to herding in section five. Section six concludes. The paper contains an appendix with supplementary material regarding the data and further results.

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 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 in 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 in system 1, and that heuristics are used to answer the question. In 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. In 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.[3] 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

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

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 in system 1, because it means that agents use preliminary future oriented results (PEXP) from others as heuristics for their own post-announcement PAGO.

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.[4] 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 of the five questions in the previous section as follows. First they calculate the percentages of positive and negative

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

replies (i.e. answers with a lower or higher label than the middle label). 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.[5] Next, they subtract percentage of negative replies from the percentage of positive replies. 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).

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

$$ICS_t = \frac{PAGO_t + PEXP_t + BUS1Y_t + BUS1Y5Y_t + DUR_t}{6.7558} + 2.0, \tag{1}$$

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.[6] 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. The average value of 85.1 indicates that 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. Figure 1 shows that the series share a common component. Recessions and expansions are clearly present. However, fluctuations are different. This is also reflected in the different standard deviations of the series. The correlations of the constituting variables between 0.70 and 0.88 (Table 1b) mean that they are closely related but not copies of each other.

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

[6] 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.

[Figure 1 about here.]

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 answer the PAGO question. 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 respondent'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_{jt}, $j = 1, \ldots, m$, and a part unrelated to this set,

$$\Delta y_{it} = \sum_{j=1}^{m} \beta_{ij} x_{jt} + \eta_{it} \tag{2}$$

where β_{ij} is the sensitivity of the respondent's financial position to variable j, and η_{it} captures the unexplained part. To answer the PAGO question, a respondent determines $y_{it} - y_{i,t-12}$ by

aggregating the time-series of a set of state variables x_{jt} combined with private information η_{it}. 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.[7]

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

To investigate how the peak-end rule influences PAGO, 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 $r = \text{ra}$ equals

$$g^{\text{ra}}(\boldsymbol{z}_t^n) = \sum_{s=1}^{n} z_{t-n+s}. \tag{3}$$

In system 2, a respondent uses the rational rule and 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

$$g^r(\boldsymbol{z}_t^n) = \begin{cases} \max\{z_{t-n+1}, \ldots, z_t\} & \text{for } r = \text{sp} \\ \max\{\sum_{s=p}^{q} z_{t-n+s}; p, q = 1, \ldots, n, p < q\} & \text{for } r = \text{mp} \\ \min\{z_{t-n+1}, \ldots, z_t\} & \text{for } r = \text{sb} \\ \min\{\sum_{s=p}^{q} z_{t-n+s}; p, q = 1, \ldots, n, p < q\} & \text{for } r = \text{mb}. \end{cases} \tag{4}$$

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.[8] We also allow for the largest cumulative increase or decrease,

[7] 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.

[8] Varey and Kahneman (1992) investigate the assessment of unpleasant experiences, Fredrickson and

as they produce the peaks and bottoms in the aggregated series. We jointly refer to these four rules as extreme rules.

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

$$g^{\text{se}}(\boldsymbol{z}_t^n) = z_t \tag{5}$$

The respondents can use these different rules to time-aggregate the state variables in Equation (2). Since each rule transforms the time series of the state variables in a different way, the strength of the relations between the PAGO series and the transformed series of the state variables can show which rules are used. We use a linear model to investigate these relations,

$$PAGO_t = \alpha + \sum_{j=1}^{m} \sum_{r \in \mathcal{R}} \beta_j^r g^r(x_{j,t-n}, \ldots, x_{jt}) + \varepsilon_t, \tag{6}$$

where α is a constant and ε_t contains the approximation error.[9] The coefficients β_j^r reflect how strong a particular rule influences the aggregation of the variable x_j. When $\beta_j^r \neq 0$ for rule r and zero for all others, the respondents only uses that particular rule in the aggregation. When $\beta_j^r \neq 0$ for several rules r, respondents vary in the rules they use when determining $PAGO_t$.

We use a linear regression to estimate the coefficients β_j^r and determine the importance of the different rules. In system 2, respondents base their answers on a complete and precise assessment of changes in their financial situation, and the rational rule should give the best explanation of $PAGO_t$. The other rules should also not help explaining $PAGO_t$ in addition to the rational rule. In system 1, one or a combination of the peak-end rules should give the best explanation of $PAGO_t$. The rational rule should then be of limited importance.

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

Kahneman (1993) the assessment of pleasant or aversive film clips, and Kahneman et al. (1993) the assessment of a painful episodes.

[9] We present a model that explicitly links Equation (2) to Equation (6) in Appendix B.

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 B.

To investigate the influence of the different rules, we construct yearly aggregates based on the transformations in Equations (3) to (5). 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 the first two with the latter 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 multi-peak and multi-bottom 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 out whether respondents answer the PAGO question in system 1 or 2, we regress the PAGO series on the yearly changes and the peak-end series that we have created. If system 2 is used, the rational rule should explain $PAGO_t$ best. In a single regression, it should generate a higher R^2 than any of the peak-end rule transformations. In a multiple regression, the coefficients for the peak-end rules should be insignificant. If system 1 is used, a peak-end series should give a higher R^2 in a single regression than the yearly change. When we add a peak-end series next to the yearly change in the regression, the coefficient on the yearly average should decrease (in modulo) and become less significant. 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 (negative or positive) and the total change during the year is a proxy for the volatility. A multiple regression of the average change and one of the extreme rules may hence show the effect of volatility. If that is the case, the effect of the extreme rule belongs to system 2 instead of 1.

We account for the effect of volatility 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. In this case, we can observe a switch in the sign of the coefficient when we move from a single regression with an extreme series to a multiple regressions where also the yearly change is included. To be more precise, we interpret a sign switch as an indication of a volatility effect, when moving from a single to a multiple regression leads to a coefficient that switches to positive for the single- or multi-peak series or negative for the single- and multi-bottom series. The yearly change is then an omitted variable in the single regression. Changes in sign may also be caused by the high correlations between the series as in Table 2b, so care is needed. Because volatility may hence be an omitted variable, we also conduct regressions that include the volatility of the explanatory variable. 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 can explain 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 an 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 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, the single-period bottom and volatility, both the ra and sb-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 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. In particular, the multi-period bottom 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 evidence for the single-period bottom series is weaker. 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. It seems that the respondents use the sb-series as a partial substitute for the ra-series. 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 in system 1 applied to financial state variables to answer the PAGO questions. Both for the S&P500 and the house price index, the explanatory power of the multi-period bottom series is higher than of the yearly change series. We show in the next subsection that these results become even stronger when we limit our analysis to respondents that have investments in the stock market or own their house. With regard to information from the bond market index and interest rates, only volatility seems to be important. This makes it impossible to find a replacement by the peak-end rule. However, fluctuations in interest rates were much stronger in the first half of our sample period, and therefore we repeat our analysis for subsamples, which we also discuss in the next subsection. 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 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 multi-period peak series point at substitution. In a single regression, the mp-coefficient has the right sign, and the 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. Contrary to the multi-period peak series, the other extreme-rule 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. 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 do not find evidence for the end-rule.

The change in non-farm payrolls (Table 4c) exhibits strong explanatory power for PAGO with an R^2 of 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 the multi-period bottom series are consistent with a partial replacement of the ra-series. 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.

We conclude that respondents pay more attention to extremes that are to their disadvan-

tage than to the yearly change when assessing changes in their financial position. This result is present for both financial and macroeconomic variables, though the strength varies. The evidence is mostly concentrated in the multiperiod extremes and not in the single-period series. However, the monthly and quarterly frequency we use in our analysis need not correspond with the frequency with which respondents have made their observations. It may very well be that respondents do not have a fixed frequency at all, but instead make irregular observations based on news. Extremes are of course likely to become news, in particular if they present a peak or bottom in a longer period. The multiperiod extremes better capture such events.

For some variables, we see that the both an extreme rule and the yearly change are significant. This result implies that the rules jointly explain PAGO. We interpret this as evidence that part of the respondents use an extreme rule, and thus system 1, where others use the rational rule, and thus system 2 to answer the PAGO question. It also means we cannot claim that all respondents use system 1, but the evidence does indicate that a substantial part of them does.

We do not find that respondents use the end rule to make their assessment. The failure to find evidence for the end rule may also be caused by a mismatch between the data frequency in our analysis, and the frequency that the respondents use. We use the most recent month or quarter to evaluate the end rule, but we do not know whether this is actually the most recent observation for the respondent. This is an important difference with for example Langer et al. (2005), where agents really observe a payment stream, or the psychological evidence in which people watch film clips or experience episodes of pain (Fredrickson and Kahneman, 1993; Fredrickson, 2000; Kahneman, 2000). In these experimental settings, the observation frequency is known, contrary to our setting.

4.4 Subsample analysis

4.4.1 Sample splits based on stock and house ownership

The results for the financial variables show that streaks of decreasing stock and house prices can explain PAGO better than changes over the whole year. If respondents truly make the substitution we propose in Equation (2), the importance of the stock and housing markets should be higher for respondents that are stronger exposed to them. Because multi-period drops in equity and house prices hurt these respondents more, we also expect stronger evi-

dence for the replacement of the rational rule by the multi-period bottom rule.

The Michigan survey has information about house and stock ownership available from January 2000 onwards. We show in Table A.3 that around 60% of the respondents invest in stocks, and 75% own their house. We use this information, combined with the weight for every respondent, to create PAGO-series based on subsamples that are split on house and stock ownership.

The results for the sample split based on stock ownership in Table 5 show that the explanatory power of changes in the S&P500 is stronger for respondents that own stocks. The coefficient for the rational rule is significant for the PAGO of this group (panel b), but insignificant for the PAGO of respondents without stocks (panel c). Consistent with our full sample results, the multi-period bottom series show stronger explanatory power than the rational rule. This effect is again stronger for the respondents with than without stocks. In a single regression with the mb-series, the R^2 are 33 and 11%. However, also for respondents without stocks large drops in the stock market explain PAGO whereas the average change has no explanatory power. This finding may indicate that large drops in the stock market signal a more general deterioration of the economy.

[Table 5 about here.]

We next analyse the effect of changes in the house price index for the sample split based on home ownership. Comparing the results for 2000–2014 in Table 6a to those for 1978–2014 in Table 3e shows the effect of the subprime mortgage crisis of 2007-2009. The explanatory power of yearly changes in the house price index rises from 23% to 71%. The single- and multi-period bottom series yield a slightly higher R^2 of 74% and 72% for the 2000–2014 period. In a multiple regression of the rational rule and the sb-rule, the rational rule loses its significance. When combined with the mb-rule, its coefficient is halved but remains significant. However, the sb and mb-rule do not add value when both the yearly change and the volatility are present.

[Table 6 about here.]

We observe only small difference between the split samples, probably because of the impact of the subprime mortgage crisis. The yearly changes in house prices explain PAGO for homeowners better (R^2 of 68% versus 60%). For both groups, the R^2 increase when the sb and mb series are used, with the increase being larger if the mb-series for homeowners is

considered (from 68 to 73% vs. from 60% to 62%). The results for the multiple regressions do not differ much. The peak series are again proxies for volatility.

4.4.2 Subperiod analyses

Our full sample period comprises subperiods that show substantial differences in the financial and macroeconomic environment. The great moderation set in in the late 1980s, the 2000s showed the burst of the IT bubble and the subprime credit crisis, which was followed by low economic growth, inflation and interest rates in the 2010s. We therefore split our sample period in two (January 1978–June 1996, and July 1996–December 2014, 222 months in each period). We repeat our analyses for both subperiods. We summarize our main findings here and report the full results in Appendix B.

Our results show that the two subperiods are indeed quite different. For the financial variables these differences are mostly related to volatility. The stock market and the housing market exhibit higher volatility in the second half, whereas the interest rates and consequently the bond market were more volatile in the first. The macroeconomic variables show mainly lower means (except for the unemployment rate), and lower volatility for inflation and economic growth.

The explanatory power of the financial variables for PAGO is related to their volatility. Changes in interest rates and in the bond market index explain PAGO in the first half and not in the second, while the stock and housing market show the reverse pattern. If the yearly change has explanatory power for PAGO, detrimental extremes perform better. The evidence that the multi-period bottom series explain PAGO better than the yearly change of the stock and housing market is concentrated in the second half. In the first period, all stock and housing market series fail to explain PAGO. To the contrary, the multi-period bottoms in the bond market work well then, as do peaks in the T-bill rate. The 10-year T-bond rate is more relevant in the second half, in particular multi-period bottoms. This result may be a particular effect of the subprime credit crisis.

The results for the macro variables present a less clear picture. The effect that inflation has on PAGO changes from positive in the first half to negative in the second. Detrimental extremes, meaning peaks in the first half and bottoms in the second, have a stronger effect on PAGO than the yearly change. The growth rates of GNP and PCE only have explanatory power in the second half, and their effect is not subsumed by the extreme or end rules. The growth rate of nonfarm payrolls explains PAGO is both subperiods. In the second

subperiod, we find some evidence for the single-bottom series being informative. Changes in the unemployment rate are informative in both halves. The evidence favoring the multi-period peak series is concentrated in the second half.

We conclude that the subperiod results enrich the patterns observed in the full sample results. First, detrimental extremes only replace yearly changes when a variable offers at least some explanatory power. If the yearly change does not explain PAGO, neither do the extremes. For the financial variables and inflation, their explanatory power relates positively to their volatility. Volatile series explain PAGO, tranquil series do not. For the other macro variables, we do not see such a pattern. Second, the effect of inflation and perhaps relatedly the interest rates reverses moving from the first to the second half. Consequently, peaks are relevant in the first half, and bottoms in the second half. Third, the evidence for the extreme rules in the macro series is weaker in our subperiod analysis, in particular for GNP and PCE growth rates. Their explanatory power is concentrated in the second half, during which the detrimental extreme series (that is bottoms for growth rates of GNP, PCE and nonfarm payrolls and peaks in the unemployment rate) show strong correlation with the yearly changes. Consequently, it is difficult to separate them.

4.5 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 7 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 7 about here.]

5 Herding

We now turn our attention to herding. As argued in Section 2, in system 2 there should be no effect of the one respondent's future expectations (PEXP, BUS1Y and BUS5Y) 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 in 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 process another respondent's expectations after they have been communicated, 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 and the coming year (or five years for BUS5Y) included in 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 announcement schedule, we create two additional series 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. 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, $PAGO_t^{\text{pa}}$ and the preliminary values of the forward-looking variables (PEXP, BUS1Y and BUS5Y), collected in a vector $\boldsymbol{x}_t^{\text{prelim}}$, by a linear regression

$$PAGO_t^{\text{pa}} = \alpha + \beta PAGO_t^{\text{prelim}} + \boldsymbol{\gamma}' \boldsymbol{x}_t^{\text{prelim}} + \boldsymbol{\delta}' \boldsymbol{z}_t + \varepsilon_t, \quad \varepsilon_t \sim \text{N}(0, \sigma^2). \tag{7}$$

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

In 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 into 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 (7). We provide details and summary statistics of the demographic variables in Appendix A.2.

5.2 Results

Table 8 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 8 about here.]

[Table 8 (continued) about here.]

We show in Appendix A.2 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 C). 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 8b 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 8c 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 8d 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 8a and significant between the 5 and 10% level. The effect of BUS1Y is still positive, with coefficients as in Table 8b, 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 $\boldsymbol{x}_t$,

$$\boldsymbol{y}_{t+1} = \boldsymbol{\psi} + \boldsymbol{\Phi}\boldsymbol{y}_t + \boldsymbol{\eta}_{t+1}, \quad \boldsymbol{\eta} \sim \mathrm{N}(\boldsymbol{0}, \boldsymbol{\Sigma}), \tag{8}$$

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 pa values,

$$\begin{pmatrix} PAGO_t^{\text{final}} \\ \boldsymbol{x}_t^{\text{final}} \end{pmatrix} = (1-w_t) \begin{pmatrix} PAGO_t^{\text{prelim}} \\ \boldsymbol{x}_t^{\text{prelim}} \end{pmatrix} + w_t \begin{pmatrix} PAGO_t^{\text{pa}} \\ \boldsymbol{x}_t^{\text{pa}} \end{pmatrix}, \tag{9}$$

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

$$\begin{aligned} IR(h, \Delta\boldsymbol{x}_t^{\text{prelim}}, \boldsymbol{y}_{t-1}) &= \mathrm{E}[\boldsymbol{y}_{t+h}|\Delta\boldsymbol{x}_t^{\text{prelim}}, \Delta PAGO_t^{\text{prelim}} = 0, \boldsymbol{y}_{t-1}] - \mathrm{E}[\boldsymbol{y}_{t+h}|\boldsymbol{y}_{t-1}] \\ &= \boldsymbol{\Phi}^h\big(\mathrm{E}[\boldsymbol{y}_t|\Delta\boldsymbol{x}_t^{\text{prelim}}, \Delta PAGO_t^{\text{prelim}} = 0, \boldsymbol{y}_{t-1}] - \mathrm{E}[\boldsymbol{y}_t|\boldsymbol{y}_{t-1}]\big). \end{aligned} \tag{10}$$

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 (7),

$$PAGO_t^{\text{pa}} = \alpha_1 + \beta_1 PAGO_t^{\text{prelim}} + \boldsymbol{\gamma}_1'\boldsymbol{x}_t^{\text{prelim}} + \boldsymbol{\delta}_1'\boldsymbol{z}_t + \varepsilon_{1,t} \tag{11}$$

$$\boldsymbol{x}_t^{\text{pa}} = \boldsymbol{\alpha}_2 + \boldsymbol{\beta}_2 PAGO_t^{\text{prelim}} + \boldsymbol{\gamma}_2\boldsymbol{x}_t^{\text{prelim}} + \boldsymbol{\delta}_2\boldsymbol{z}_t + \boldsymbol{\varepsilon}_{2,t}, \tag{12}$$

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 $\boldsymbol{x}_t^{\text{pa}}$ can be rationally influenced by both $PAGO_t^{\text{prelim}}$ and $\boldsymbol{x}_t^{\text{prelim}}$, there are no coefficient restrictions in Equation (12) in either system 1 or 2.

The expected effect of the shock on $PAGO_t^{\text{pa}}$ in system 1 follows from Equation (11) as

$$\mathrm{E}_{\mathrm{S1}}\left[PAGO_t^{\text{pa}}|\Delta \boldsymbol{x}_t^{\text{prelim}}, \Delta PAGO_t^{\text{prelim}} = 0, \boldsymbol{y}_{t-1}\right] - \mathrm{E}_{\mathrm{S1}}\left[PAGO_t^{\text{pa}}|\boldsymbol{y}_{t-1}\right] = \boldsymbol{\gamma}_1' \Delta \boldsymbol{x}_t^{\text{prelim}}. \quad (13)$$

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

$$\mathrm{E}_{\mathrm{S2}}\left[PAGO_t^{\text{pa}}|\Delta \boldsymbol{x}_t^{\text{prelim}}, \Delta PAGO_t^{\text{prelim}} = 0, \boldsymbol{y}_{t-1}\right] - \mathrm{E}_{\mathrm{S2}}\left[PAGO_t^{\text{pa}}|\boldsymbol{y}_{t-1}\right] = 0. \quad (14)$$

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

$$\begin{aligned}&\mathrm{E}_{\mathrm{S1}}\left[\boldsymbol{x}_t^{\text{pa}}|\Delta \boldsymbol{x}_t^{\text{prelim}}, \Delta PAGO_t^{\text{prelim}} = 0, \boldsymbol{y}_{t-1}\right] - \mathrm{E}_{\mathrm{S1}}\left[\boldsymbol{x}_t^{\text{pa}}|\boldsymbol{y}_{t-1}\right] = \\ &\mathrm{E}_{\mathrm{S2}}\left[\boldsymbol{x}_t^{\text{pa}}|\Delta \boldsymbol{x}_t^{\text{prelim}}, \Delta PAGO_t^{\text{prelim}} = 0, \boldsymbol{y}_{t-1}\right] - \mathrm{E}_{\mathrm{S2}}\left[\boldsymbol{x}_t^{\text{pa}}|\boldsymbol{y}_{t-1}\right] = \boldsymbol{\gamma}_2 \Delta \boldsymbol{x}_t^{\text{prelim}}. \quad (15)\end{aligned}$$

With Equation (9) 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 (8) and (12) in Tables C.3 and C.4 in Appendix C. In Figure 2 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 differ much, 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 (9). The dotted lines in panels (a–c) give the effect that the shock has in system 2. Because of the restriction in Equation (14), 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 (9) and (13), the lines start above zero because the γ_1-coefficients reported in the first column of each panel of Table 8 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 show in Table 8, the effects of shocks in BUS1Y and BUS5Y are smaller, but still exceed 6-7% over that horizon.

[Figure 2 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,

$$\begin{aligned} &\mathrm{E}[\Delta \boldsymbol{x}_t | \Delta x_{it}^{\text{prelim}}, \Delta PAGO_t^{\text{prelim}} = 0, \boldsymbol{y}_{t-1}] \\ =&\mathrm{E}[\boldsymbol{x}_t^{\text{prelim}} | \Delta x_{it}^{\text{prelim}}, \Delta PAGO_t^{\text{prelim}} = 0, \boldsymbol{y}_{t-1}] - \mathrm{E}[\boldsymbol{x}_t^{\text{prelim}} | \boldsymbol{y}_{t-1}], \end{aligned} \tag{16}$$

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 (16). We report the estimation results in Table C.5.

The results of this impulse response analysis in Figure 3 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 8d also shows that the herding effect is less clear-cut when it can run via PEXP, BUS1Y and BUS5Y combined. Still, Figure 3d 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 3 about here.]

5.4 Robustness checks

We show in Appendix A that all sentiment variables exhibit a high degree of persistence. This near unit-root behavior may lead to spurious regression results in our analysis so far. Therefore, we repeat our tests for changes in the different variables,

$$\Delta PAGO_t^{\text{pa}} = \alpha + \beta \Delta PAGO_t^{\text{prelim}} + \boldsymbol{\gamma}' \Delta \boldsymbol{x}_t^{\text{prelim}} + \boldsymbol{\delta}' \boldsymbol{z}_t + \varepsilon_t, \quad \varepsilon_t \sim \mathrm{N}(0, \sigma^2). \tag{17}$$

For both the dependent and the explanatory sentiment variables we take the difference with respect to the final value of that variable in the previous period, which we denote with the Δ-operator in front of them. In system 2 we still expect $\boldsymbol{\gamma} = 0$. We also test whether $\Delta PAGO_t^{\text{prelim}}$ is an unbiased predictor of $\Delta PAGO_t^{\text{pa}}$.

Our results for changes in PEXP in Table 9a confirm the results in Table 8a. We reject the hypothesis $\gamma = 0$ for all regressions in which $\Delta PAGO_t^{\text{pa}}$ is the dependent variable. The inclusion of covariates does not change this result. For the longer $\Delta PAGO_t^{\text{np}}$ series the effect is weaker (p-value of 0.13). For all series we reject that $\Delta PAGO_t^{\text{prelim}}$ is an unbiased predictor of $\Delta PAGO_t^{\text{np}}$ and $\Delta PAGO_t^{\text{pa}}$. These results mean that we also find that the increased optimism of one group of respondents about their future financial position spills over into the assessment by another group about their past financial position, when we concentrate on changes.

[Table 9 about here.]

[Table 9 (continued) about here.]

The results for BUS1Y and BUS5Y in Table 9b and c show that we do not find this effect for changes in expectations about business conditions. The coefficients for $\Delta BUS1Y^{\text{prelim}}$ and $\Delta BUS5Y^{\text{prelim}}$ are close to zero and insignificant. In Table 8, the effects of BUS1Y and BUS5Y were also weaker than for PEXP, but mostly (marginally) significant. We reject the hypothesis that $\Delta PAGO_t^{\text{prelim}}$ is an unbiased predictor of $\Delta PAGO_t^{\text{np}}$ and $\Delta PAGO_t^{\text{pa}}$, but this is largely driven by the estimates for c and $\Delta PAGO_t^{\text{prelim}}$.

When we include the changes in all three forward-looking sentiment variables in the regression (Table 9d) the coefficient of $\Delta PEXP^{\text{prelim}}$ is large and significant, whereas the coefficients for $\Delta BUS1Y^{\text{prelim}}$ and $\Delta BUS5Y^{\text{prelim}}$ are again insignificant. These results do not change when covariates are included. Moreover, the results for the joint test $\boldsymbol{\gamma} = \mathbf{0}$ (reported in the row "Wald2") further support the relation from future expectations to past assessments. Also here we reject that $\Delta PAGO_t^{\text{prelim}}$ is an unbiased predictor.

We conclude that the result we report in Table 8 are not spurious. Also when we conduct the analysis based on changes, we find that future expectations of one group influence the past assessment of another group about their financial position, on top of what could be expected based the past assessments of this first group. This result holds in particular when the future expectation is also about the financial position. The influence is weaker when expectations about business conditions are considered.

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. We rule out that the explanatory power of the extremes stems from the risk aversion of the respondents. Second, respondents' assessment of past changes can be predicted by the expectation about future changes of other respondents that are interviewed earlier beyond how these respondents assessed past changes. The predictability by expected future changes increases when we correct for systematic demographic differences between the groups of respondents.

The cognitive biases we find can be understood in the judgmental framework of Tversky and Kahneman (1974) where agents make quick intuitive judgments under system 1, instead of more reasoned ones 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 these cognitive biases are not restricted to individual behavior, but also affect an important economic indicator such as the ICS. They complement earlier findings of the peak-end rule and herding that were confined to more controlled or even laboratory settings. As a second contribution, we argue that the presence of a subjective behavioral component can explain why indexes of consumer sentiment constitute an important economic indicator next to more objectively defined macro variables. Other explanations state that they contain news that is not yet present in other macro variables or that they capture sudden changes in the preferences of consumers. Instead, their added value may stem from measuring how cognitive biases systematically impact the judgments of consumers about the economy, and consequently their actions.

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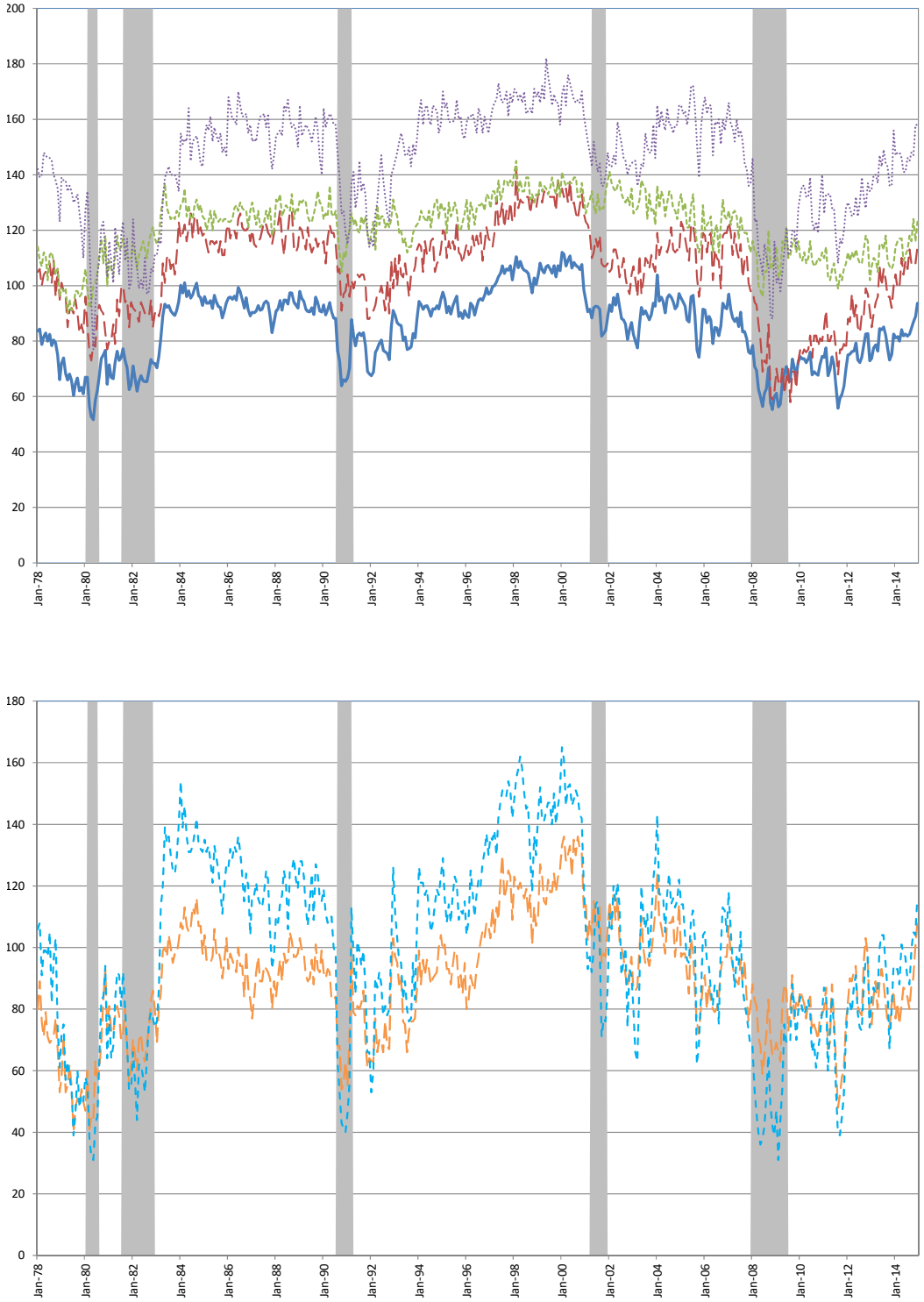
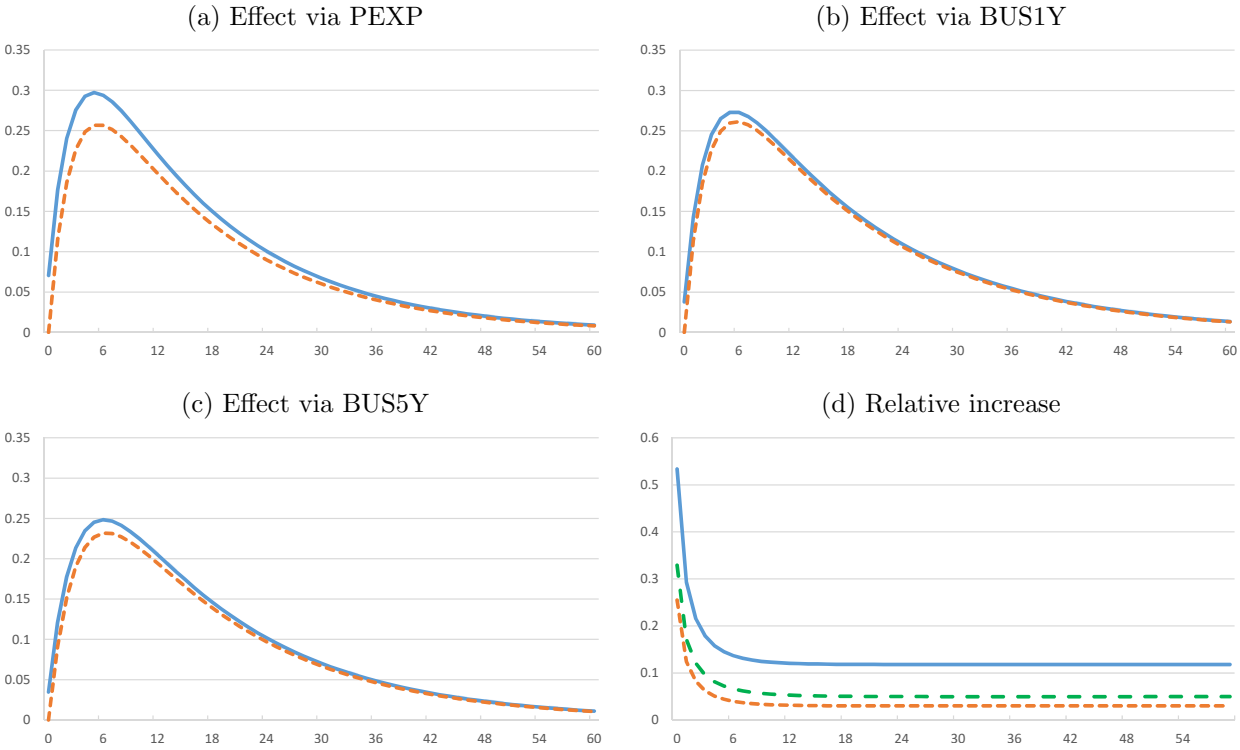
Figure 1: Evolution of ICS variables



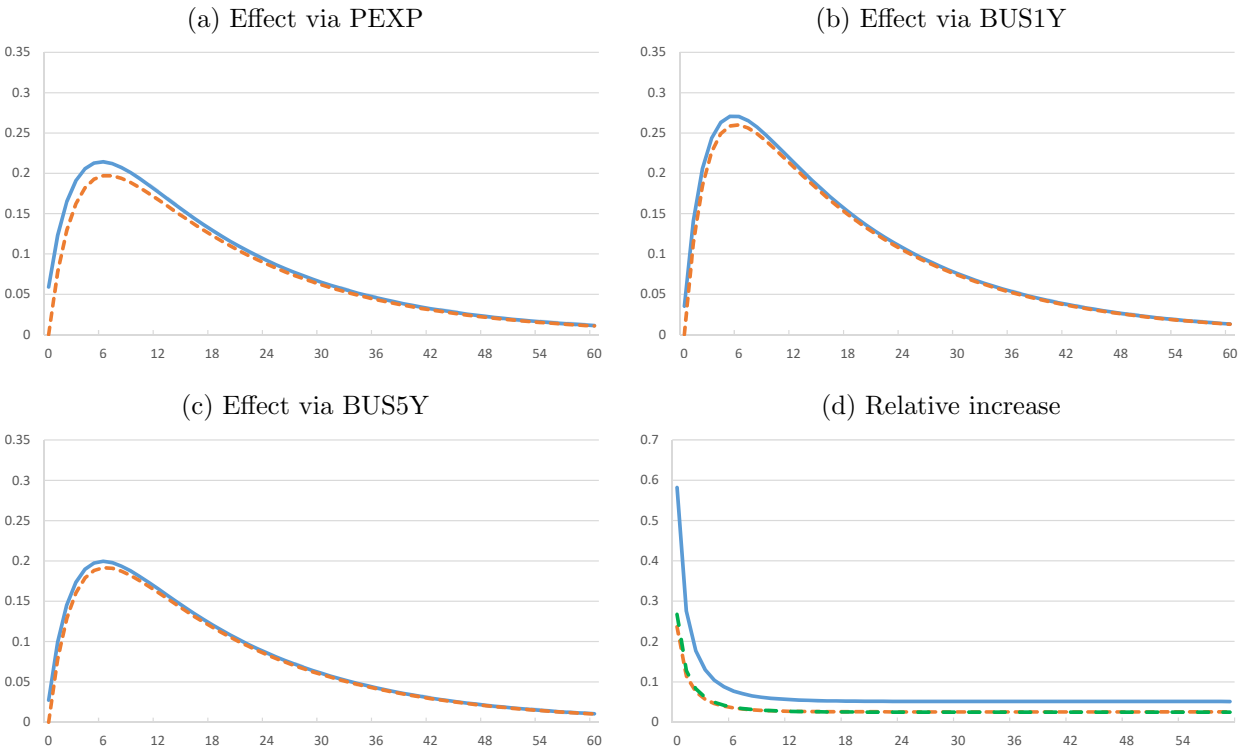
This figure shows the monthly values for ICS (blue, solid line), PAGO (red, long-dashed line), PEXP (green, short-dashed line) and DUR (purple, dotted line) in the top panel, and BUS1Y (light blue, short-dashed line), BUS5Y (orange, long-dashed line) in the bottom panel over the period January 1978 –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

Figure 2: 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 (10) and (15) combined with Equation (13) in system 1 (solid blue line) or with Equation (14) in system 2 (orange dotted line). The esimates for $\boldsymbol{\Phi}$ in Equation (10) are reported in Table C.3(a), the estimates for γ_1 in Table 8, and the estimates for γ_2 in Table C.4, 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 3: 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 (16), 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 C.5. 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 (10) and (15) combined with Equation (13) in system 1 (solid blue line) or with Equation (14) in system 2 (orange dotted line). The esimates for $\boldsymbol{\Phi}$ in Equation (10) are reported in Table C.3(a), the estimates for γ_1 in Table 8, and the estimates for γ_2 in Table C.4(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 (3), the extreme rules in Equation (4) and the end rule in Equation (5). 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 B.1 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 (3). The row g^{r} contains the coefficient estimates for one of the peak-end rules in Equations (4) and (5) 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 (3). The row g^{r} contains the coefficient estimates for one of the peak-end rules in Equations (4) and (5) 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 (×100)

rule	ra		sp			mp			sb			mb			end		
g^{ra}	-0.08^{***}	-0.07^{***}		-0.07^{***}	-0.08^{***}		0.00	-0.02		-0.10^{***}	-0.06^{***}		-0.12^{***}	-0.10^{***}		-0.08^{***}	-0.07^{***}
	(0.01)	(0.02)		(0.02)	(0.02)		(0.03)	(0.03)		(0.01)	(0.02)		(0.02)	(0.02)		(0.01)	(0.02)
g^{r}			-0.43^{***}	-0.15	0.24	-0.13^{***}	-0.13^{***}	-0.09^{**}	-0.28	0.22	-0.11	-0.08^{*}	0.14^{***}	0.10^{*}	-0.21^{***}	-0.02	-0.04
			(0.13)	(0.12)	(0.21)	(0.02)	(0.04)	(0.05)	(0.23)	(0.18)	(0.23)	(0.04)	(0.05)	(0.05)	(0.07)	(0.03)	(0.03)
vol.		-0.21^{***}			-0.35^{**}			-0.12			-0.25^{**}			-0.12			-0.22^{***}
		(0.07)			(0.14)			(0.07)			(0.11)			(0.07)			(0.07)
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: Tests Results of the Peak and End Rules Applied to the S&P500 Depending on Investment in Stocks

(a) All respondents

rule	ra		sp			mp			sb			mb			end		
g^{ra}	0.28	−0.04		0.26	−0.32		0.60***	0.62		−0.42**	−0.59***		−0.77***	−0.97***		0.29	−0.07
	(0.21)	(0.26)		(0.23)	(0.21)		(0.15)	(0.42)		(0.19)	(0.17)		(0.28)	(0.29)		(0.21)	(0.26)
g^{r}			−1.85	−1.61	4.20	−0.69	−1.45***	−1.49**	2.49***	3.92***	7.37***	0.68***	1.55***	2.19***	0.24	−0.13	0.28
			(1.58)	(1.65)	(2.70)	(0.44)	(0.24)	(0.63)	(0.43)	(0.61)	(1.77)	(0.14)	(0.25)	(0.56)	(0.52)	(0.37)	(0.37)
vol.		−1.58***			−3.26***			0.06			2.24*			1.13			−1.64***
		(0.60)			(0.88)			(1.06)			(1.16)			(0.96)			(0.62)
R^2	0.08	0.23	0.04	0.11	0.30	0.08	0.35	0.35	0.34	0.40	0.47	0.28	0.42	0.44	0.00	0.07	0.23

(b) Respondents with investment in stocks

rule	ra		sp			mp			sb			mb			end		
g^{ra}	0.39*	0.04		0.37	−0.27		0.76***	0.80*		−0.39*	−0.57***		−0.78**	−1.00***		0.39*	−0.02
	(0.22)	(0.28)		(0.24)	(0.23)		(0.15)	(0.47)		(0.21)	(0.20)		(0.30)	(0.33)		(0.23)	(0.28)
g^{r}			−2.17	−1.84	4.59	−0.69	−1.65***	−1.71**	3.05***	4.37***	8.09***	0.85***	1.73***	2.42***	0.52	0.00	0.46
			(1.80)	(1.86)	(2.96)	(0.50)	(0.26)	(0.73)	(0.43)	(0.68)	(2.16)	(0.14)	(0.27)	(0.68)	(0.57)	(0.40)	(0.40)
vol.		−1.78***			−3.62***			0.11			2.42*			1.23			−1.87***
		(0.67)			(0.98)			(1.22)			(1.39)			(1.15)			(0.70)
R^2	0.11	0.27	0.05	0.15	0.33	0.06	0.39	0.38	0.38	0.43	0.48	0.33	0.44	0.46	0.01	0.11	0.27

(c) Respondents without investment in stocks

rule	ra		sp			mp			sb			mb			end		
g^{ra}	0.09	−0.14		0.08	−0.43**		0.36**	0.49		−0.49**	−0.70***		−0.81***	−1.10***		0.12	−0.13
	(0.21)	(0.25)		(0.22)	(0.22)		(0.16)	(0.42)		(0.20)	(0.17)		(0.28)	(0.29)		(0.21)	(0.26)
g^{r}			−0.89	−0.82	4.35	−0.75**	−1.20***	−1.43**	1.60***	3.27***	7.39***	0.41**	1.33***	2.24***	−0.19	−0.35	−0.07
			(1.52)	(1.57)	(2.80)	(0.37)	(0.25)	(0.64)	(0.48)	(0.59)	(1.76)	(0.17)	(0.25)	(0.55)	(0.47)	(0.37)	(0.36)
vol.		−1.17**			−2.90***			0.42			2.67**			1.63*			−1.15*
		(0.58)			(0.90)			(1.07)			(1.16)			(0.94)			(0.61)
R^2	0.00	0.10	0.01	0.01	0.18	0.11	0.21	0.21	0.15	0.26	0.35	0.11	0.28	0.33	0.00	0.01	0.09

This table shows the results of regressions of $PAGO_t$ constructed for different subsamples of respondents, on changes of the S&P500 index that have been transformed based on different rules. In panel (a) the dependent variable is $PAGO_t$ based on all respondents. In the other panels we construct the PAGO-series based on the subsamples of respondents with or without investments in the stock market (panels b and c). We calculate the values for PAGO as given by Equation (B.2) using weights as reported by the Michigan survey. The row g^{ra} contains the coefficient estimates for the rational rule of Equation (3). The row g^{r} contains the coefficient estimates for one of the peak-end rules in Equations (4) and (5) 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 2000 to December 2014 ($T = 179$). Information about stock ownership is missing for all respondents in May 2003.

Table 6: Tests Results of the Peak and End Rules Applied to the House Price index Depending on Home Ownership

(a) All respondents

rule	ra		sp			mp			sb			mb			end		
g^{ra}	2.87***	2.07***		4.18***	1.78**		5.16***	3.56***		0.47	2.04***		1.40**	1.50***		3.27***	2.43***
	(0.29)	(0.24)		(0.68)	(0.81)		(0.90)	(1.11)		(0.89)	(0.71)		(0.61)	(0.55)		(0.34)	(0.32)
g^{r}			12.11***	−7.19**	1.20	4.07***	−3.86**	−2.09	8.93***	7.54***	0.10	6.66***	3.74**	2.02	8.16***	−1.64	−1.41
			(1.97)	(2.98)	(2.99)	(0.78)	(1.49)	(1.68)	(0.83)	(2.88)	(2.62)	(0.50)	(1.47)	(1.45)	(1.09)	(1.15)	(0.98)
vol.		−6.73***			−7.38***			−4.63*			−6.68***			−4.89**			−6.65***
		(2.17)			(2.39)			(2.53)			(2.55)			(2.30)			(2.20)
R^2	0.71	0.76	0.50	0.74	0.76	0.55	0.75	0.77	0.74	0.73	0.76	0.72	0.75	0.77	0.47	0.71	0.76

(b) Respondents who own or are buying a house, weighted averages

rule	ra		sp			mp			sb			mb			end		
g^{ra}	2.91***	2.09***		4.22***	1.63*		5.33***	3.73***		0.56	2.27***		0.23	0.90		3.46***	2.59***
	(0.31)	(0.27)		(0.74)	(0.93)		(1.03)	(1.28)		(0.96)	(0.76)		(1.00)	(0.97)		(0.38)	(0.34)
g^{r}			12.32***	−7.18**	1.87	4.12***	−4.08**	−2.30	9.06***	7.39**	−0.70	5.67***	5.25***	2.88	8.14***	−2.22*	−1.98*
			(2.00)	(3.25)	(3.44)	(0.81)	(1.73)	(1.96)	(0.89)	(3.10)	(2.82)	(0.40)	(1.93)	(1.95)	(1.19)	(1.34)	(1.14)
vol.		−6.95***			−7.96***			−4.62*			−7.27***			−4.57*			−6.83***
		(2.35)			(2.65)			(2.65)			(2.76)			(2.43)			(2.38)
R^2	0.68	0.73	0.48	0.71	0.73	0.52	0.73	0.74	0.70	0.70	0.73	0.73	0.73	0.74	0.44	0.69	0.74

(c) Respondents who are renting, weighted averages

rule	ra		sp			mp			sb			mb			end		
g^{ra}	2.69***	2.02***		3.98***	2.46***		4.35***	2.75***		0.12	1.07		0.84	1.53**		2.53***	1.80***
	(0.26)	(0.23)		(0.57)	(0.68)		(0.63)	(0.96)		(0.77)	(0.73)		(0.63)	(0.62)		(0.31)	(0.32)
g^{r}			11.30***	−7.11***	−1.78	3.89***	−2.80***	−1.02	8.43***	8.06***	3.60	5.15***	3.62***	1.19	8.22***	0.65	0.85
			(1.86)	(2.68)	(2.65)	(0.70)	(0.99)	(1.25)	(0.68)	(2.52)	(2.71)	(0.36)	(1.25)	(1.56)	(0.82)	(0.93)	(0.91)
vol.		−5.66***			−4.70**			−4.63*			−4.01*			−4.68*			−5.71***
		(1.94)			(2.05)			(2.69)			(2.42)			(2.72)			(1.93)
R^2	0.60	0.63	0.41	0.62	0.63	0.48	0.62	0.63	0.63	0.62	0.63	0.62	0.62	0.63	0.46	0.60	0.63

This table shows the results of regressions of $PAGO_t$ constructed for different subsamples of respondents, on changes of the house price index that have been transformed based on different rules. In panel (a) the dependent variable is $PAGO_t$ based on all respondents. In the other panels we construct the PAGO-series based on the subsamples of respondents who own or are buying a house or those who are renting (panels b and c). We calculate the values for PAGO as given by Equation (B.2) using weights as reported by the Michigan survey. The row g^{ra} contains the coefficient estimates for the rational rule of Equation (3). The row g^{r} contains the coefficient estimates for one of the peak-end rules in Equations (4) and (5) 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 ($T = 180$).

Table 7: 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, $\Delta x_{j,t-11}, \ldots, \Delta x_{jt}$ 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 (3). The row g^{end} contains the coefficient estimates for the end rules in Equation (5). 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 8: Test of the Herding Effect

(a) Effect via PEXP

	$PAGO^{\text{np}}$	$PAGO^{\text{pa}}$	$PAGO^{\text{pa}}$	$PAGO^{\text{pa}}$	$PAGO^{\text{pa}}$	$PAGO^{\text{pa}}$
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)
$PAGO^{\text{prelim}}$	0.79^{***}	0.85^{***}	0.86^{***}	0.83^{***}	0.82^{***}	0.82^{***}
	(0.06)	(0.07)	(0.06)	(0.06)	(0.06)	(0.06)
$PEXP^{\text{prelim}}$	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

	$PAGO^{\text{np}}$	$PAGO^{\text{pa}}$	$PAGO^{\text{pa}}$	$PAGO^{\text{pa}}$	$PAGO^{\text{pa}}$	$PAGO^{\text{pa}}$
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)
$PAGO^{\text{prelim}}$	0.74^{***}	0.82^{***}	0.84^{***}	0.82^{***}	0.81^{***}	0.82^{***}
	(0.09)	(0.10)	(0.09)	(0.09)	(0.09)	(0.08)
$BUS1Y^{\text{prelim}}$	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 $PAGO_t^{\text{np}}$ and $PAGO_t^{\text{pa}}$ on a constant, $PAGO_t^{\text{prelim}}$, 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. $PAGO_t^{\text{pa}}$ is based on the interviews taken after the announcement of the preliminary values, and is available from January 2000 onwards. To create the $PAGO_t^{\text{np}}$ series, we augment the $PAGO_t^{\text{pa}}$ 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 $PAGO_t^{\text{prelim}}$ 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 $PAGO_t^{\text{np}}$ and $PAGO_t^{\text{pa}}$ are based on 288 and 180 observations.

Table 8: Test of the Herding Effect – *continued*

(c) Effect via BUS5Y

	$PAGO^{\text{np}}$	$PAGO^{\text{pa}}$	$PAGO^{\text{pa}}$	$PAGO^{\text{pa}}$	$PAGO^{\text{pa}}$	$PAGO^{\text{pa}}$
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)
$PAGO^{\text{prelim}}$	0.81***	0.90***	0.90***	0.88***	0.87***	0.87***
	(0.07)	(0.07)	(0.06)	(0.07)	(0.07)	(0.06)
$BUS1Y5Y^{\text{prelim}}$	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

	$PAGO^{\text{np}}$	$PAGO^{\text{pa}}$	$PAGO^{\text{pa}}$	$PAGO^{\text{pa}}$	$PAGO^{\text{pa}}$	$PAGO^{\text{pa}}$
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)
$PAGO^{\text{prelim}}$	0.71***	0.79***	0.80***	0.78***	0.77***	0.77***
	(0.09)	(0.09)	(0.08)	(0.09)	(0.09)	(0.08)
$PEXP^{\text{prelim}}$	0.13	0.22*	0.22*	0.24*	0.25**	0.25**
	(0.09)	(0.13)	(0.13)	(0.13)	(0.13)	(0.12)
$BUS1Y^{\text{prelim}}$	0.10	0.15	0.14	0.12	0.12	0.10
	(0.07)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)
$BUS5Y^{\text{prelim}}$	−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.

Table 9: Test of the Herding Effect on Changes

(a) Effect via changes in PEXP

	$\Delta PAGO^{\text{np}}$	$\Delta PAGO^{\text{pa}}$	$\Delta PAGO^{\text{pa}}$	$\Delta PAGO^{\text{pa}}$	$\Delta PAGO^{\text{pa}}$	$\Delta PAGO^{\text{pa}}$
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)
$\Delta PAGO^{\text{prelim}}$	0.49^{***}	0.52^{***}	0.55^{***}	0.52^{***}	0.54^{***}	0.57^{***}
	(0.10)	(0.14)	(0.14)	(0.14)	(0.14)	(0.13)
$\Delta PEXP^{\text{prelim}}$	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

	$\Delta PAGO^{\text{np}}$	$\Delta PAGO^{\text{pa}}$	$\Delta PAGO^{\text{pa}}$	$\Delta PAGO^{\text{pa}}$	$\Delta PAGO^{\text{pa}}$	$\Delta PAGO^{\text{pa}}$
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)
$\Delta PAGO^{\text{prelim}}$	0.52^{***}	0.63^{***}	0.66^{***}	0.63^{***}	0.65^{***}	0.68^{***}
	(0.10)	(0.14)	(0.13)	(0.13)	(0.13)	(0.12)
$\Delta BUS1Y^{\text{prelim}}$	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 $PAGO_t^{\text{np}}$ and $PAGO_t^{\text{pa}}$ on a constant, changes in $PAGO_t^{\text{prelim}}$, 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 $\Delta PAGO_t^{\text{np}}$ and $\Delta PAGO_t^{\text{pa}}$ are based on 288 and 180 observations. See Table 8 for further explanation.

Table 9: Test of the Herding Effect on Changes – *continued*

(c) Effect via changes in BUS5Y

	$\Delta PAGO^{\text{np}}$	$\Delta PAGO^{\text{pa}}$	$\Delta PAGO^{\text{pa}}$	$\Delta PAGO^{\text{pa}}$	$\Delta PAGO^{\text{pa}}$	$\Delta PAGO^{\text{pa}}$
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)
$\Delta PAGO^{\text{prelim}}$	0.52***	0.64***	0.65***	0.62***	0.65***	0.66***
	(0.10)	(0.13)	(0.13)	(0.13)	(0.13)	(0.12)
$\Delta BUS5Y^{\text{prelim}}$	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

	$\Delta PAGO^{\text{np}}$	$\Delta PAGO^{\text{pa}}$	$\Delta PAGO^{\text{pa}}$	$\Delta PAGO^{\text{pa}}$	$\Delta PAGO^{\text{pa}}$	$\Delta PAGO^{\text{pa}}$
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)
$\Delta PAGO^{\text{prelim}}$	0.48***	0.55***	0.58***	0.55***	0.57***	0.60***
	(0.10)	(0.14)	(0.14)	(0.14)	(0.14)	(0.13)
$\Delta PEXP^{\text{prelim}}$	0.16	0.36***	0.35***	0.35***	0.36***	0.34**
	(0.11)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)
$\Delta BUS1Y^{\text{prelim}}$	0.02	−0.03	−0.06	−0.08	−0.05	−0.09
	(0.07)	(0.10)	(0.10)	(0.10)	(0.09)	(0.09)
$\Delta BUS5Y^{\text{prelim}}$	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.

A Additional Data Analysis

A.1 Index of Consumer Sentiment Data

We investigate the time-series properties of the different ICS variables 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.

[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 Demographic variables in the CAB survey

Table A.2 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.2 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,

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

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.3 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.3 about here.]

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-g) 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)				

See table note on previous page.

Table A.2: 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.3: 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 ($\times$ 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 ($\times$ 1,000)	180	66.47	9.00	70.20	10.44	3.79^{***}	(0.54)
Invamt ($\times$ 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 Supplement for the peak-end analysis

B.1 Methodological details

In this section, we provide a model that shows the effect of the rules that respondents can use to answer the PAGO questions on the aggregate PAGO value. Our starting point is the interpretation of the PAGO question as an ordered choice model. We assume that each respondent i determines the change in her financial position. We label this variables $PAGO^*_{it} = y_{it} - y_{i,t-12}$. She use thresholds to transform it to the ordered categorical variable

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

with $\gamma_{i,1} < \gamma_{i,2}$. The aggregate $PAGO_t$ is calculated as a weighted average of $PAGO_{it}$, centered such that if all respondents report $PAGO_{it} = 3$ the result is 100,

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

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.

We assume that the respondent uses state variables to answer the PAGO question. In system 2, the agent use the rational rule and calculates

$$PAGO^{\text{ra}}_{it} = y_{it} - y_{i,t-12} = \sum_{s=0}^{11} \Delta y_{i,t-s} = \sum_{s=0}^{11} \sum_{j=1}^{m} \beta_{ij} x_{j,t-s} + \eta_{i,t-s}, \tag{B.3}$$

based on Equation (2), which is then used for $PAGO^*_{it}$ in Equation (B.1). In system 1, the respondent can use a combination of the peak-end rules of Section 4 to answer the PAGO question, which means

$$PAGO^*_{it} = \sum_{r \in \mathcal{R}} \sum_{j=1}^{m} \beta^r_{i,j} g^r(\boldsymbol{x}^n_{j,t}) + \sum_{r \in \mathcal{R}} \beta^r_{i,0} g^r(\boldsymbol{\eta}^n_{it}) \tag{B.4}$$

is used in Equation (B.1). To determine how the rules influence the aggregate $PAGO_t$, we substitute Equation (B.4) in Equation (B.2),

$$PAGO_t = 100 \sum_{i=1}^{n} w_i \left(I\left(\sum_{j=1}^{m} \sum_{r \in \mathcal{R}} \beta_{i,j}^r g^r(\boldsymbol{x}_{j,t}^n) + \sum_{r \in \mathcal{R}} \beta_{i,0}^r g^r(\boldsymbol{\eta}_{it}^n) \geq \gamma_{i,1} \right) + I\left(\sum_{j=0}^{m} \sum_{r \in \mathcal{R}} \beta_{i,j}^r g^r(\boldsymbol{x}_{j,t}^n) + \sum_{r \in \mathcal{R}} \beta_{i,0}^r g^r(\boldsymbol{\eta}_{it}^n) \geq \gamma_{i,2} \right) \right). \tag{B.5}$$

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 the linear approximation in Equation (6) to investigate the effects of the different rules. Because the idiosyncratic parts η_{it} are unobservable, we include their effect in α and ε_t.

B.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 B.1. 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 B.1 about here.]

B.3 Subperiod analyses

We split our sample period in two halves: January 1978–June 1996 and July 1996-December 2014. Both subperiods have 222 observations.

B.3.1 Financial variables

The summary statistics in Table B.2 show pronounced differences between the two subperiods. The equity and housing market show lower average returns and higher volatilities in

the second subperiod. For the bond market, the average returns is higher and the volatility lower in the second half. The volatilities of the 3-month T-bill and the 10-year bond rates are also considerably lower in the second half. However, they also show lower average changes.

[Table B.2 about here.]

The differences between the extreme series show the combined effect of the difference in means and volatilities. The peak series for the stock and housing market behave similarly over the subperiods. The bottom series, in particular the multiperiod one, show lower averages and higher volatility in the second half. For the bond market and the interest rates, the extreme series are substantially more extreme in the first half. The correlations in Table B.2b show small variations compared to the full sample results.

Table B.3a shows that none of the stock market series has explanatory power for PAGO in the first half. To the contrary, the stock market explains PAGO significantly in the second half (Table B.4a). The yearly average has a coefficient of 0.46 which is larger than in the full sample (0.35), and leads to a higher R^2. The effect of the multi-period bottom series is also stronger than in the full sample analysis, and more clearly dominates the rational rule. It leads to a higher R^2 in the single regression. In the multiple regressions with the mb-series, the ra-series is not significant anymore. We also see a clear volatility effect with the right sign. The single bottom series and the end series are not very informative, whereas the peak series are a proxy for volatility.

[Table B.3 about here.]

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

[Table B.4 about here.]

[Table B.4 (continued) about here.]

The explanatory power of the bond market is concentrated in the first half, though the yearly change itself is not significant. Both the single-period and multiperiod bottom series are significant with R^2 around 15%. The coefficients have the wrong sign to be a proxy for volatility, but their effects vanish when volatility is included. The peak-series do proxy for volatility. We do not see an effect of the end rule.

Using the short rate leads to quite different results for the two subperiods. In the first half, the yearly change has no explanatory power for PAGO, though the volatility has. The single peak series has a very large and significantly negative effect on PAGO with an R^2 of 41%. The effect is unaffected by volatility. The results for the multi-period peak series point in the same direction. The bottom series are a proxy for volatility. In the second half, rises in the short rate have a positive effect on PAGO. However, the extreme rules do no give better results than the rational rule. The bottom series proxy for volatility. The end series are insignificant in both halves. The difference between the subperiods may be related to the high inflation in the first half and the low economic growth in the second.

The results for the 10-year interest rate for the first half resemble those for the short rate. The rational rule does not explain PAGO, but the single period peak, and to a lesser extent the multi-period peak series do. Overall, the explanatory power is smaller and more related to volatility. The second half shows a different picture. The rational rule has no effect on PAGO, but now the single bottom series, and to a lesser extent the multi-period bottom series have. They do not proxy for volatility, whereas the peak series do. The result for the second half may be related to quantitative easing which targeted the long-term interest rate.

The effects of the house price index are again concentrated in the second half of the sample period. In the first half, only the volatility of the housing market matters. The extreme rules show up significantly in multiple regressions, but their effect is related to volatility. In the second half, the housing market is very important to explain PAGO. The rational rule leads to an R^2 of 58% and the multi-period bottom even to 69%. Both the single-period and the multi-period bottom series explain PAGO better than the rational rule. Part of their effect is driven by volatility, but the effect of the mb-series does not disappear in the presence of volatility. Both the peak series and the end series are a proxy for volatility. Of course, these differences are due to the presence of the subprime credit crisis in the second half.

B.3.2 Macro variables

Table B.5 shows that the behavior of the macro variables considerably differs between the two subperiods. During the first period, the growth rates of CPI, GNP, NFP and PCE exhibit means that are around a factor 2 larger than during the second period. The standard deviation of inflation is also markedly lower in the second subperiod. The growth rates of GNP and NFP are a bit less volatile during the second subperiod, whereas PCE shows higher volatility. Contrary to these four variables, the unemployment rate does not show

large difference between the two subperiods. The differences in the other four variables can be explained by the great moderation setting in after the 1980s.

[Table B.5 about here.]

Also here, the differences between the extreme series reflect the differences in means and volatilities. Because means and volatilities are higher in the first subperiod for CPI, GNP, NFP and PCE, their peak-series have higher averages and standard deviations. For the bottom series these differences affect the averages in opposite directions, resulting in averages that are much closer. The standard deviations of the extreme series do not differ much between the two subperiods. The extreme series for the change in the unemployment rate are quite similar over the two subperiods in both means and standard deviations. Variations in correlations with the rational rule reported in Table B.5 are small compared to the full sample results, except for the single-peak series in CPI, and the bottom series for PCE. The bottom series for GNP, NFP and PCE are more correlated with the yearly changes in the second half.

The results for inflation in Table B.6a and Table B.7a present very different pictures. In the first half, yearly inflation has a negative effect on PAGO, which is highly significant and strong with an R^2 of 50%. The single peak series explains PAGO even better, and drives out the effect of the yearly change. The results for the multi-period peak series are unreliable because of the strong correlation between the ra- and mp-series. The bottom series are mainly a proxy for volatility. In the second half, yearly inflation does not explain PAGO. However, both the single and multi-period bottom series can explain PAGO (R^2 around 30%). Their effects are related to volatility, but are not subsumed by it. Contrary to the first half, the peak series are now a proxy for volatility. The positive coefficients of the bottom series indicate that higher inflation has a positive effect on PAGO, whereas the effect was negative in the first half. It indicates that respondents were averse to high inflation in the first half and averse to deflation in the second half. In both halfs, the detrimental extremes (so peaks in the first and bottoms in the second) are more informative than the yearly change. The end series cannot replace the yearly change.

[Table B.6 about here.]

[Table B.6 (continued) about here.]

[Table B.7 about here.]

[Table B.7 (continued) about here.]

The explanatory power of GNP growth also shows marked differences between the two halves. In the first half, none of the GNP growth series explains PAGO. In the second half, yearly GNP growth rates have a significantly positive effect on PAGO. The extreme rules and the end rule do not lead to higher explanatory power.

The growth rate of nonfarm payrolls explains PAGO in both subperiods, with a stronger effect in the second half (R^2 goes up from 18 to 49%.) The multi-period peak and bottom series are highly correlated with the yearly growth rates, so there explanatory power is similar to the it, but we do not find evidence for replacement. In the second subperiod, we see some evidence for a joint use of the yearly growth rate and the single-bottom series. There is also some evidence for a joint role for the yearly growth rate and the end-series in the first period.

The results for the unemployment rate differ less between the two halves, compared to the other macro variables. In both supperiods, the unemployment rate has a negative effect on PAGO. The explanatory power is a bit larger during the first half. The peak- and the end-series can explain PAGO as well, but the yearly change is more informative. The bottom series are a proxy for volatility. In the second subperiod, the multi-period peak series is more informative than the yearly change. It subsumes the effect of the yearly change in a multiple regression, also when volatility is included. For the single peak series, the evidence is less clear cut. The bottom series proxy again for volatility, and the end rule has only a small effect.

The results for PCE grwoth look like the results for GNP growth. There is no effect in the first subperiod, but a strong effect in the second. The bottom series can explain PAGO, but not as good as the yearly change. The peak series proxy for volatility.

Table B.1: 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 B.2: Subperiod Summary Statistics of Financial Variables and their Peak and End Rule Transformations

(a) Means and standard deviations

		SP500		LABI		UST3M		UST10Y		HPIQ	
change in		log		log		level		level		log	
subsample		1st	2nd	1st	2nd	1st	2nd	1st	2nd	1st	2nd
ra	mean	9.83	6.24	0.17	0.57	-0.01	-0.28	-0.07	-0.20	5.17	3.14
	stdev	12.89	18.75	7.22	3.16	2.30	1.29	1.73	0.75	3.21	4.92
sp	mean	7.28	6.55	3.02	1.51	0.66	0.17	0.54	0.35	1.99	1.62
	stdev	2.73	2.06	2.20	0.58	0.72	0.14	0.34	0.14	1.00	0.98
mp	mean	17.73	18.03	6.48	3.59	1.74	0.46	1.30	0.72	5.21	4.40
	stdev	8.79	8.70	4.55	1.62	1.95	0.54	0.99	0.38	3.17	3.07
sb	mean	-6.73	-7.06	-2.99	-1.74	-0.87	-0.26	-0.61	-0.38	0.60	0.02
	stdev	5.02	4.48	1.54	0.79	1.16	0.28	0.44	0.22	0.86	1.63
mb	mean	-9.53	-13.26	-6.18	-3.23	-1.82	-0.71	-1.40	-0.87	0.65	-0.48
	stdev	7.68	13.40	4.50	1.74	2.10	1.03	1.06	0.45	0.86	2.66
end	mean	0.88	0.51	0.01	0.07	0.00	-0.02	0.00	-0.02	1.24	0.80
	stdev	4.25	4.56	1.99	0.99	0.66	0.19	0.40	0.22	0.92	1.42

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

	SP500		LABI		UST3M		UST10Y		HPIQ	
subsample	1st	2nd	1st	2nd	1st	2nd	1st	2nd	1st	2nd
sp	0.28	-0.04	0.10	0.29	0.24	0.07	0.45	0.41	0.94	0.89
mp	0.78	0.62	0.60	0.77	0.52	0.57	0.76	0.76	1.00	0.94
sb	0.45	0.60	0.42	0.38	0.26	0.82	0.30	0.50	0.91	0.97
mb	0.64	0.85	0.73	0.80	0.47	0.90	0.70	0.82	0.92	0.95
end	0.26	0.32	0.34	0.29	0.30	0.51	0.35	0.30	0.82	0.86

This table shows summary statistics of the series of the financial variables that have been transformed according to different rules, given in the rows, corresponding with the first and second half of the sample period. The rational rule is given in Equation (3), the extreme rules in Equation (4) and the end rule in Equation (5). 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 half of the sample period runs from January 1978 to June 1996. The second half runs from July 1996 to December 2014. Both periods have 222 observations. See Table B.1 for more information on the source and nature of the explanatory variables.

Table B.3: Tests Results of the Peak and End Rules based on Financial Variables, first half of the sample period

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

rule	ra		sp			mp			sb			mb			end		
g^{ra}	0.12	0.11		0.14	0.18		0.12	0.09		0.15	0.25		0.14	0.23		0.12	0.12
	(0.15)	(0.16)		(0.16)	(0.20)		(0.29)	(0.34)		(0.18)	(0.20)		(0.20)	(0.20)		(0.16)	(0.16)
g^{r}			−0.25	−0.44	−0.68	0.13	−0.01	0.04	0.00	−0.17	−1.37	0.10	−0.05	−0.43	0.07	−0.03	−0.02
			(0.65)	(0.68)	(1.12)	(0.22)	(0.41)	(0.45)	(0.49)	(0.58)	(1.14)	(0.34)	(0.43)	(0.64)	(0.17)	(0.17)	(0.17)
vol.		−0.05			0.18			−0.08			−1.12			−0.48			−0.05
		(0.49)			(0.71)			(0.58)			(0.77)			(0.67)			(0.49)
R^2	0.01	0.01	0.00	0.01	0.01	0.00	0.01	0.00	0.00	0.01	0.04	0.00	0.01	0.01	0.00	0.01	0.00

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

rule	ra		sp			mp			sb			mb			end		
g^{ra}	0.33	0.22		0.41	0.35		0.82***	0.10		0.05	0.29		−0.32	0.31		0.38	0.24
	(0.35)	(0.27)		(0.28)	(0.31)		(0.30)	(0.41)		(0.30)	(0.30)		(0.38)	(0.41)		(0.36)	(0.28)
g^{r}			−2.29***	−2.43***	−1.74	−0.52	−1.30***	0.25	3.27**	3.18**	−1.12	1.06**	1.44**	−0.23	−0.02	−0.49	−0.21
			(0.67)	(0.58)	(2.81)	(0.47)	(0.43)	(0.88)	(1.31)	(1.43)	(3.11)	(0.43)	(0.56)	(0.74)	(0.53)	(0.43)	(0.34)
vol.		−1.65***			−0.50			−1.92*			−2.09*			−1.84***			−1.63***
		(0.50)			(2.09)			(1.11)			(1.19)			(0.65)			(0.50)
R^2	0.03	0.20	0.15	0.20	0.20	0.03	0.17	0.19	0.15	0.15	0.20	0.14	0.15	0.19	0.00	0.03	0.19

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

rule	ra		sp			mp			sb			mb			end		
g^{ra}	0.02	−0.19		0.91	0.96		2.17***	1.64		−0.88	0.04		−1.77**	−0.75		−0.09	−0.25
	(1.05)	(0.81)		(0.68)	(0.78)		(0.72)	(1.15)		(0.85)	(0.85)		(0.84)	(0.94)		(1.07)	(0.82)
g^{r}			−11.23***	−11.91***	−12.50*	−3.54***	−4.87***	−3.79*	6.32***	6.78***	−2.13	3.31***	4.22***	1.51	1.17	1.26	0.79
			(1.98)	(1.82)	(7.00)	(0.79)	(0.56)	(2.08)	(0.78)	(0.91)	(2.81)	(0.53)	(0.56)	(3.00)	(1.63)	(1.38)	(0.73)
vol.		−4.64***			0.26			−1.11			−6.00***			−3.04			−4.62***
		(0.54)			(2.60)			(2.06)			(1.99)			(3.43)			(0.53)
R^2	0.00	0.38	0.41	0.43	0.43	0.29	0.40	0.40	0.33	0.35	0.38	0.30	0.37	0.38	0.00	−0.01	0.38

This table shows the results of regressions of $PAGO_t$ on changes of financial variables over the past year that have been transformed based on different rules for the first half of the sample period. 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 (3). The row g^{r} contains the coefficient estimates for one of the peak-end rules in Equations (4) and (5) 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 June 1996 ($T = 222$).

Table B.3: Tests Results of the Peak and End Rules based on Financial Variables, first half of the sample period – *continued*

(d) Changes in the 10-year bond yield

rule	ra		sp			mp			sb			mb			end		
g^{ra}	−1.43	−1.28		−0.04	−0.92		1.12	−2.43		−2.39**	−2.47**		−3.68**	0.46		−1.62	−1.39
	(1.43)	(1.11)		(1.22)	(1.40)		(1.80)	(1.89)		(1.15)	(1.21)		(1.49)	(1.85)		(1.50)	(1.17)
g^{r}			−15.62***	−15.52***	−4.39	−4.38**	−5.86*	2.75	9.99***	12.76***	13.66	1.08	5.25**	−3.88	−0.17	2.27	1.38
			(5.27)	(5.92)	(13.49)	(2.18)	(3.13)	(3.90)	(3.80)	(3.42)	(9.89)	(2.19)	(2.40)	(3.68)	(2.92)	(2.60)	(1.96)
vol.		−7.68***			−5.80			−9.99***			0.61			−11.78***			−7.63***
		(2.64)			(6.02)			(2.78)			(7.91)			(3.84)			(2.63)
R^2	0.03	0.19	0.17	0.17	0.18	0.11	0.12	0.19	0.11	0.21	0.20	0.00	0.13	0.19	0.00	0.03	0.18

(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}	−0.64	−0.11		4.89***	2.65**		14.63**	−2.61		−4.29***	−0.38		−5.23***	0.37		−1.42	−0.69
	(0.59)	(0.48)		(1.20)	(1.21)		(6.30)	(7.71)		(1.08)	(0.86)		(0.98)	(2.93)		(0.96)	(0.73)
g^{r}			−4.25**	−18.88***	−10.10**	−0.68	−15.46**	2.54	0.55	15.01***	1.02	0.77	18.71***	−1.80	−0.75	3.31	2.41
			(1.77)	(3.77)	(4.96)	(0.58)	(6.45)	(7.86)	(2.94)	(4.44)	(3.77)	(2.95)	(3.78)	(11.11)	(1.63)	(2.26)	(1.65)
vol.		−13.07***			−8.39**			−13.36***			−12.53***			−14.16*			−12.91***
		(2.27)			(3.26)			(2.53)			(2.93)			(7.43)			(2.20)
R^2	0.02	0.32	0.11	0.29	0.35	0.02	0.05	0.31	0.00	0.20	0.31	0.00	0.27	0.31	0.00	0.04	0.32

See Table note on the previous page.

Table B.4: Tests Results of the Peak and End Rules based on Financial Variables, second half of the sample period

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

rule	ra		sp			mp			sb			mb			end		
g^{ra}	0.46***	0.40*		0.45**	0.42		0.66***	0.98***		0.37	0.38		0.00	−0.46		0.47***	0.41
	(0.17)	(0.24)		(0.18)	(0.29)		(0.16)	(0.34)		(0.28)	(0.28)		(0.39)	(0.30)		(0.18)	(0.25)
g^{r}			−1.00	−0.84	−0.36	0.17	−0.71	−1.29**	1.50	0.56	0.51	0.75***	0.75*	2.06***	0.48	−0.13	−0.06
			(1.61)	(1.57)	(2.81)	(0.53)	(0.47)	(0.60)	(0.97)	(1.17)	(2.26)	(0.14)	(0.45)	(0.44)	(0.45)	(0.27)	(0.30)
vol.		−0.36			−0.25			1.00			−0.04			2.14**			−0.35
		(0.74)			(1.29)			(0.86)			(1.43)			(0.85)			(0.76)
R^2	0.18	0.19	0.01	0.18	0.18	0.00	0.24	0.26	0.11	0.19	0.18	0.25	0.25	0.32	0.01	0.18	0.18

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

rule	ra		sp			mp			sb			mb			end		
g^{ra}	−1.52	−1.71*		−1.22	−1.90		0.63	0.45		−1.88*	−1.45		−3.28*	−2.70*		−1.55	−1.77*
	(1.02)	(0.94)		(1.13)	(1.46)		(1.72)	(1.67)		(1.04)	(1.15)		(1.73)	(1.42)		(1.04)	(0.96)
g^{r}			−7.67	−5.75	2.50	−4.51**	−5.45	−5.06	0.98	3.82	−4.13	−0.77	3.98	2.43	−1.11	0.33	0.54
			(7.07)	(8.31)	(14.09)	(2.01)	(3.33)	(3.10)	(3.99)	(4.38)	(8.51)	(2.48)	(3.66)	(3.30)	(1.50)	(1.32)	(1.28)
vol.		−4.10			−5.30			−0.62			−6.74			−2.28			−4.13
		(3.94)			(6.08)			(3.07)			(7.84)			(3.76)			(3.97)
R^2	0.05	0.09	0.04	0.08	0.09	0.13	0.13	0.13	0.00	0.07	0.09	0.00	0.09	0.10	0.00	0.05	0.09

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

rule	ra		sp			mp			sb			mb			end		
g^{ra}	5.41**	8.85***		5.19*	13.91**		3.79	12.51		12.72***	14.66***		11.92**	8.52		5.97**	9.39***
	(2.53)	(3.06)		(3.11)	(5.35)		(3.86)	(8.58)		(4.02)	(4.86)		(5.12)	(6.07)		(2.84)	(3.27)
g^{r}			31.43	27.80	−54.45	11.87***	6.77	−7.60	7.49	−41.09**	−71.48*	4.49	−9.05	0.67	13.52	−7.51	−7.28
			(33.61)	(29.62)	(49.66)	(4.53)	(7.65)	(13.11)	(15.75)	(19.59)	(36.88)	(3.70)	(7.53)	(13.66)	(9.43)	(8.86)	(8.51)
vol.		19.39			45.50*			29.77			−19.54			20.26			19.36
		(14.61)			(23.64)			(25.46)			(26.68)			(26.08)			(14.56)
R^2	0.12	0.18	0.04	0.15	0.20	0.10	0.14	0.19	0.01	0.22	0.23	0.05	0.16	0.18	0.01	0.12	0.18

This table shows the results of regressions of $PAGO_t$ on changes of financial variables over the past year that have been transformed based on different rules for the second half of the sample period. 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 (3). The row g^{r} contains the coefficient estimates for one of the peak-end rules in Equations (4) and (5) 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 July 1996 to December 2014 ($T = 222$).

Table B.4: Tests Results of the Peak and End Rules based on Financial Variables, second half of the sample period – *continued*

(d) Changes in the 10-year bond yield

rule	ra		sp			mp			sb			mb			end		
g^{ra}	5.48	4.53		6.75	1.43		11.30*	0.07		−1.35	−3.28		−4.88	1.25		5.59	4.49
	(4.32)	(4.18)		(4.38)	(5.56)		(6.25)	(7.08)		(4.73)	(5.15)		(7.02)	(6.03)		(4.50)	(4.38)
g^{r}			−1.71	−17.20	35.61	1.75	−15.09	10.73	44.63***	46.90***	64.49***	14.51**	21.27**	7.16	4.27	−1.28	0.49
			(21.67)	(22.30)	(32.85)	(9.67)	(12.81)	(12.89)	(7.29)	(9.06)	(19.30)	(6.93)	(10.49)	(10.52)	(6.34)	(6.41)	(6.39)
vol.		−27.65**			−41.32**			−36.92**			18.13			−21.67			−27.68**
		(13.91)			(18.11)			(17.37)			(17.76)			(17.74)			(14.00)
R^2	0.04	0.13	0.00	0.05	0.15	0.00	0.07	0.14	0.24	0.24	0.25	0.10	0.11	0.13	0.00	0.03	0.13

(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}	3.07***	1.55***		5.83***	2.31***		6.93***	3.20***		−2.02	1.22		−1.46	0.27		3.36***	1.80***
	(0.43)	(0.29)		(0.74)	(0.86)		(0.93)	(1.22)		(1.31)	(0.95)		(0.91)	(0.71)		(0.55)	(0.44)
g^{r}			10.36***	−15.58***	−3.02	3.93***	−6.58***	−2.27	9.91***	15.80***	1.27	6.20***	8.78***	3.16**	8.88***	−1.17	−0.98
			(2.84)	(3.54)	(3.48)	(1.03)	(1.51)	(1.68)	(1.07)	(4.26)	(3.47)	(0.48)	(1.82)	(1.51)	(1.30)	(1.30)	(1.03)
vol.		−12.13***			−10.38***			−9.69***			−11.53***			−9.36***			−12.11***
		(2.34)			(2.57)			(3.24)			(2.53)			(2.78)			(2.37)
R^2	0.58	0.73	0.26	0.70	0.73	0.36	0.69	0.74	0.66	0.68	0.73	0.69	0.70	0.74	0.40	0.58	0.73

See Table note on the previous page.

Table B.5: Summary Statistics of Macro Variables and their Peak and End Rule Transformations

(a) Means and standard deviations

		CPI		GNP		NFP		UNEMP		PCE	
change in		log		log		log		level		log	
subsample		1st	2nd	1st	2nd	1st	2nd	1st	2nd	1st	2nd
ra	mean	5.09	2.32	7.45	4.86	1.96	0.90	-0.09	0.04	7.11	4.71
	stdev	3.04	1.15	2.70	2.37	1.93	1.75	1.07	1.09	1.97	2.15
sp	mean	0.76	0.63	2.87	2.11	0.55	0.36	0.34	0.24	1.93	1.38
	stdev	0.34	0.23	1.18	1.11	0.25	0.25	0.18	0.13	0.67	0.39
mp	mean	5.14	2.60	7.45	5.00	2.38	1.40	0.67	0.61	7.31	5.02
	stdev	3.00	0.89	2.70	2.12	1.36	0.91	0.66	0.84	1.96	1.67
sb	mean	0.08	-0.27	1.02	0.43	-0.21	-0.18	-0.31	-0.25	-0.57	-0.35
	stdev	0.26	0.39	0.67	0.73	0.27	0.29	0.12	0.10	0.60	0.52
mb	mean	0.04	-0.42	1.08	0.45	-0.48	-0.51	-0.72	-0.55	-0.62	-0.48
	stdev	0.36	0.76	0.69	0.82	0.72	1.01	0.53	0.32	0.62	0.89
end	mean	0.42	0.19	1.84	1.19	0.16	0.08	-0.01	0.00	0.59	0.39
	stdev	0.33	0.31	1.03	0.89	0.27	0.22	0.21	0.18	0.76	0.54

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

	CPI		GNP		NFP		UNEMP		PCE	
subsample	1st	2nd	1st	2nd	1st	2nd	1st	2nd	1st	2nd
sp	0.88	0.31	0.81	0.77	0.73	0.71	0.58	0.84	0.63	0.45
mp	1.00	0.78	1.00	0.99	0.96	0.90	0.88	0.96	0.98	0.94
sb	0.68	0.57	0.63	0.77	0.69	0.80	0.47	0.63	0.08	0.66
mb	0.62	0.62	0.70	0.82	0.87	0.92	0.77	0.71	0.07	0.76
end	0.75	0.25	0.62	0.63	0.54	0.64	0.39	0.49	0.27	0.33

This table shows summary statistics of the series of the financial variables that have been transformed according to different rules, given in the rows, corresponding with the first and second half of the sample period. The rational rule is given in Equation (3), the extreme rules in Equation (4) and the end rule in Equation (5). 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 half of the sample period runs from January 1978 (PCE: January 1981) to June 1996. The second half runs from July 1996 to December 2014. Both periods have 222 observations (PCE first period 186). See Table B.1 for more information on the source and nature of the explanatory variables.

Table B.6: Tests Results of the Peak and End Rules based on Macro Variables, first half of the sample period

(a) Changes in the log of CPI

rule	ra		sp			mp			sb			mb			end		
g^{ra}	-2.97^{***}	-2.67^{***}		-1.27	-1.66		-4.99	-14.48^{***}		-3.65^{***}	-2.57^{***}		-3.30^{***}	-1.50^{**}		-3.15^{***}	-2.74^{***}
	(0.28)	(0.33)		(0.82)	(1.22)		(4.28)	(4.46)		(0.49)	(0.57)		(0.48)	(0.60)		(0.35)	(0.34)
g^{r}			-26.99^{***}	-17.05^{**}	-12.04	-2.99^{***}	2.05	12.09^{**}	-17.01^{**}	11.57^{*}	-1.30	-12.89^{***}	4.50	-11.75^{**}	-19.37^{***}	2.17	0.74
			(3.56)	(8.32)	(13.73)	(0.30)	(4.49)	(4.75)	(7.39)	(6.01)	(8.18)	(4.49)	(4.65)	(4.81)	(4.59)	(3.17)	(2.88)
vol.		-8.27^{**}			-2.99			-11.21^{***}			-8.99			-17.21^{***}			-8.21^{**}
		(4.00)			(6.52)			(3.97)			(6.77)			(5.72)			(3.96)
R^2	0.50	0.54	0.53	0.54	0.54	0.50	0.50	0.56	0.12	0.53	0.54	0.13	0.51	0.56	0.25	0.50	0.54

(b) Changes in the log of the GNP

rule	ra		sp			mp			sb			mb			end		
g^{ra}	-0.92	-0.82		-0.78	-0.94					-1.59^{**}	-3.04		-1.76^{**}	-5.74^{**}		-1.11	-1.02
	(0.88)	(1.11)		(1.64)	(1.60)					(0.80)	(1.98)		(0.86)	(2.73)		(0.95)	(1.10)
g^{r}			-1.83	-0.39	0.48	-0.92			0.32	4.31	9.54	-0.14	4.71	18.96^{**}	-1.00	0.81	1.01
			(1.57)	(3.15)	(3.87)	(0.88)			(3.95)	(3.93)	(6.53)	(3.76)	(3.98)	(8.53)	(1.62)	(1.42)	(1.42)
vol.		-0.62			-0.91						3.92			8.86			-0.83
		(2.60)			(3.22)						(4.11)			(5.41)			(2.73)
R^2	0.03	0.03	0.02	0.03	0.03	0.03	0.14	0.14	0.00	0.06	0.08	0.00	0.06	0.13	0.00	0.03	0.03

(c) Changes in the log of nonfarm payrolls

rule	ra		sp			mp			sb			mb			end		
g^{ra}	2.80^{***}	2.76^{***}		5.08^{***}	5.94^{***}		5.23^{**}	4.60^{*}		3.99^{***}	6.36^{***}		2.55	3.39^{*}		2.29^{**}	2.19^{**}
	(0.85)	(0.87)		(1.08)	(1.24)		(2.10)	(2.45)		(0.80)	(1.09)		(1.62)	(1.87)		(0.90)	(0.94)
g^{r}			4.50	-23.93^{***}	-32.45^{**}	3.54^{***}	-3.59	-2.70	7.37	-12.51^{**}	-39.25^{***}	6.70^{***}	0.76	-1.98	15.67^{***}	6.77^{*}	7.51^{**}
			(11.98)	(9.09)	(12.98)	(1.35)	(3.38)	(3.81)	(7.66)	(5.51)	(10.50)	(1.93)	(3.54)	(4.59)	(4.38)	(3.45)	(3.56)
vol.		-5.70			9.47			-4.28			-29.27^{**}			-7.38			-6.46
		(9.89)			(9.52)			(10.73)			(11.58)			(11.75)			(9.31)
R^2	0.18	0.18	0.00	0.28	0.29	0.14	0.18	0.19	0.02	0.21	0.34	0.14	0.17	0.18	0.11	0.19	0.20

This table shows the results of regressions of $PAGO_t$ on changes of macro variables over the past year that have been transformed based on different rules for the first half of the sample period. 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 (3). The row g^{r} contains the coefficient estimates for one of the peak-end rules in Equations (4) and (5) 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 July 1996 ($T = 222$). For PCE from January 1981 to July 1996 (T) $= 186$). Multiple regression results for the mp-series of GNP growth are missing because of multicollinearity.

Table B.6: Tests Results of the Peak and End Rules based on Macro Variables, first half of the sample period – *continued*

(d) Changes in the unemployment rate (×100)

rule	ra		sp			mp			sb			mb			end		
g^{ra}	-0.07^{***}	-0.06^{***}		-0.06^{***}	-0.07^{***}		-0.05^{**}	-0.08^{***}		-0.08^{***}	-0.05^{***}		-0.09^{***}	-0.05^{**}		-0.07^{***}	-0.06^{***}
	(0.01)	(0.01)		(0.01)	(0.01)		(0.02)	(0.03)		(0.01)	(0.01)		(0.02)	(0.03)		(0.01)	(0.01)
g^{r}			-0.32^{***}	-0.10	0.13	-0.12^{***}	-0.05	0.03	-0.27	0.07	-0.16	-0.10^{***}	0.03	-0.02	-0.17^{***}	-0.03	-0.04
			(0.09)	(0.11)	(0.17)	(0.02)	(0.04)	(0.06)	(0.16)	(0.13)	(0.14)	(0.03)	(0.04)	(0.05)	(0.04)	(0.03)	(0.03)
vol.		-0.14^{***}			-0.22^{**}			-0.18^{**}			-0.19^{***}			-0.16^{**}			-0.14^{***}
		(0.05)			(0.10)			(0.09)			(0.07)			(0.08)			(0.05)
R^2	0.39	0.43	0.21	0.40	0.44	0.36	0.40	0.44	0.06	0.39	0.44	0.18	0.39	0.43	0.08	0.39	0.44

(e) Changes in the log of personal consumption expenditures

rule	ra		sp			mp			sb			mb			end		
g^{ra}	0.70	0.45		-0.30	-0.30		1.85	3.27		0.69	-0.49		0.65	-1.01		0.72	0.47
	(1.30)	(1.45)		(1.97)	(1.98)		(2.32)	(2.15)		(1.31)	(2.07)		(1.30)	(1.91)		(1.33)	(1.49)
g^{r}			4.04^{*}	4.58	4.77	0.63	-1.18	-3.02	0.34	0.16	7.15	2.07	1.92	11.15	0.08	-0.19	-0.17
			(2.32)	(4.99)	(5.69)	(1.34)	(2.72)	(3.21)	(3.57)	(3.49)	(7.91)	(3.88)	(3.90)	(7.37)	(1.04)	(0.84)	(0.86)
vol.		1.49			-0.22			2.22			6.19			8.84			1.49
		(2.37)			(3.10)			(2.79)			(6.33)			(6.24)			(2.38)
R^2	0.01	0.01	0.05	0.05	0.04	0.01	0.01	0.02	-0.01	0.00	0.04	0.01	0.01	0.12	-0.01	0.00	0.01

See Table note on the previous page.

Table B.7: Tests Results of the Peak and End Rules based on Macro Variables, second half of the sample period

(a) Changes in the log of CPI

rule	ra		sp			mp			sb			mb			end		
g^{ra}	3.25	0.46		5.43**	−3.31		13.83***	4.27		−3.21	−3.47		−3.96	−2.17		3.01	0.39
	(3.60)	(2.91)		(2.64)	(4.80)		(1.68)	(4.73)		(3.59)	(4.39)		(3.64)	(4.42)		(3.81)	(2.96)
g^{r}			−27.88	−36.36**	33.70	−3.46	−17.51***	−5.20	28.44***	33.83***	36.35	13.69***	17.40***	10.06	6.32	3.45	1.18
			(18.81)	(16.39)	(30.96)	(4.17)	(4.18)	(6.54)	(4.28)	(8.31)	(25.80)	(1.96)	(3.92)	(11.73)	(5.61)	(6.42)	(3.20)
vol.		−21.47***			−34.93**			−16.33*			1.74			−9.62			−21.42***
		(5.36)			(14.11)			(9.07)			(16.47)			(15.73)			(5.31)
R^2	0.03	0.30	0.10	0.18	0.32	0.02	0.26	0.30	0.31	0.33	0.32	0.27	0.30	0.31	0.01	0.03	0.30

(b) Changes in the log of the GNP

rule	ra		sp			mp			sb			mb			end		
g^{ra}	5.46***	5.64***		5.63***	4.43***		6.95*	5.05		4.81***	5.70***		4.94***	8.97**		5.01***	5.16***
	(0.87)	(0.90)		(1.35)	(1.00)		(3.82)	(4.57)		(1.26)	(1.88)		(1.47)	(3.64)		(0.82)	(0.89)
g^{r}			8.85***	−0.48	4.10*	6.00***	−1.69	0.69	14.79***	2.74	−0.21	13.61***	1.84	−10.07	10.33***	1.92	2.08
			(2.54)	(2.74)	(2.27)	(1.18)	(4.82)	(6.01)	(3.50)	(4.81)	(7.01)	(2.46)	(4.40)	(9.88)	(3.19)	(2.24)	(2.03)
vol.		−1.78			−4.47			−1.91			−1.88			−6.80			−1.89
		(2.41)			(2.77)			(2.89)			(3.44)			(5.30)			(2.41)
R^2	0.42	0.43	0.24	0.42	0.43	0.41	0.42	0.42	0.29	0.42	0.42	0.31	0.42	0.43	0.21	0.42	0.43

(c) Changes in the log of nonfarm payrolls

rule	ra		sp			mp			sb			mb			end		
g^{ra}	8.01***	7.51***		9.38***	7.59***		6.01***	2.98		5.77***	6.43***		9.63**	11.61***		7.63***	7.00***
	(1.13)	(1.20)		(1.38)	(2.83)		(2.12)	(2.51)		(1.59)	(1.88)		(3.89)	(3.87)		(1.08)	(1.11)
g^{r}			32.94***	−13.41*	−0.65	14.70***	4.33	9.20	45.39***	17.20**	10.09	12.18***	−3.05	−8.21	44.00***	4.86	6.28
			(12.41)	(7.93)	(18.39)	(3.53)	(5.98)	(6.16)	(9.65)	(7.19)	(13.63)	(1.81)	(5.60)	(5.89)	(11.00)	(6.97)	(6.39)
vol.		−12.10**			−11.73			−18.86***			−6.48			−18.52***			−12.45**
		(5.61)			(12.98)			(5.50)			(9.92)			(5.27)			(5.61)
R^2	0.49	0.51	0.17	0.51	0.51	0.44	0.50	0.54	0.42	0.51	0.51	0.38	0.50	0.53	0.23	0.49	0.51

This table shows the results of regressions of $PAGO_t$ on changes of macro variables over the past year that have been transformed based on different rules for the second half of the sample period. 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 (3). The row g^{r} contains the coefficient estimates for one of the peak-end rules in Equations (4) and (5) 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 July 1996 to December 2014 ($T = 222$).

Table B.7: Tests Results of the Peak and End Rules based on Macro Variables, second half of the sample period – *continued*

(d) Changes in the unemployment rate

rule	ra		sp			mp			sb			mb			end		
g^{ra}	-0.09^{***}	-0.06^{**}		-0.04	-0.07^{**}		0.14	0.10		-0.12^{***}	-0.04		-0.18^{***}	-0.16^{***}		-0.09^{***}	-0.05^{*}
	(0.02)	(0.03)		(0.04)	(0.03)		(0.09)	(0.08)		(0.02)	(0.05)		(0.02)	(0.03)		(0.02)	(0.03)
g^{r}			-0.77^{***}	-0.48	0.17	-0.14^{***}	-0.31^{***}	-0.24^{**}	-0.32	0.54	-0.18	-0.02	0.42^{***}	0.37^{***}	-0.27^{*}	0.00	-0.07
			(0.27)	(0.37)	(0.45)	(0.02)	(0.10)	(0.10)	(0.50)	(0.49)	(0.65)	(0.13)	(0.11)	(0.11)	(0.16)	(0.07)	(0.05)
vol.		-0.51^{**}			-0.57^{**}			-0.30			-0.59^{*}			-0.15			-0.52^{**}
		(0.21)			(0.28)			(0.20)			(0.33)			(0.19)			(0.22)
R^2	0.25	0.35	0.26	0.28	0.35	0.35	0.39	0.42	0.02	0.29	0.35	0.00	0.47	0.47	0.06	0.25	0.35

(e) Changes in the log of personal consumption expenditures

rule	ra		sp			mp			sb			mb			end		
g^{ra}	7.06^{***}	7.14^{***}		6.69^{***}	6.22^{***}		7.51^{***}	8.63^{***}		6.70^{***}	5.81^{***}		6.98^{***}	6.28^{***}		6.99^{***}	7.07^{***}
	(0.57)	(0.61)		(0.63)	(1.07)		(1.17)	(1.62)		(0.78)	(0.71)		(0.99)	(1.08)		(0.56)	(0.61)
g^{r}			21.07^{***}	4.48	8.46	8.49^{***}	-0.60	-1.96	20.69^{**}	2.31	10.10^{*}	13.15^{***}	0.27	3.06	10.09^{***}	0.91	0.78
			(6.85)	(4.77)	(7.92)	(1.20)	(1.83)	(2.17)	(8.29)	(4.68)	(5.90)	(1.99)	(2.15)	(3.29)	(3.30)	(1.77)	(1.87)
vol.		1.72			-3.56			2.97			8.26^{*}			4.55			1.65
		(2.99)			(4.45)			(3.30)			(4.62)			(4.42)			(3.03)
R^2	0.58	0.58	0.17	0.59	0.59	0.51	0.58	0.58	0.29	0.58	0.59	0.34	0.58	0.58	0.07	0.58	0.58

See Table note on the previous page.

C Additional results for the herding analysis

[Table C.1 about here.]

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

[Table C.2 about here.]

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

[Table C.3 about here.]

[Table C.4 about here.]

[Table C.4 (continued) about here.]

[Table C.5 about here.]

Table C.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*, *BUS1Y*1*Y* 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.2 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 C.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 C.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 C.1 for further explanations.

Table C.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 C.3: 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 C.4: Estimation results for the predictive models for the forward-looking variables

(a) PEXP as dependent variable

	$PEXP^{\text{np}}$	$PEXP^{\text{pa}}$	$PEXP^{\text{pa}}$	$PEXP^{\text{np}}$	$PEXP^{\text{pa}}$	$PEXP^{\text{pa}}$
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)
$PEXP^{\text{prelim}}$	0.62***	0.78***	0.77***	0.46***	0.76***	0.75***
	(0.06)	(0.07)	(0.07)	(0.07)	(0.08)	(0.08)
$BUS1Y1Y^{\text{prelim}}$				−0.01	0.00	0.00
				(0.04)	(0.05)	(0.05)
$BUS5Y^{\text{prelim}}$				0.23***	0.03	0.03
				(0.05)	(0.07)	(0.07)
$PAGO^{\text{prelim}}$	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

	$BUS1Y1Y^{\text{np}}$	$BUS1Y1Y^{\text{pa}}$	$BUS1Y1Y^{\text{pa}}$	$BUS1Y1Y^{\text{np}}$	$BUS1Y1Y^{\text{pa}}$	$BUS1Y1Y^{\text{pa}}$
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)
$PEXP^{\text{prelim}}$				−0.07	−0.01	−0.01
				(0.11)	(0.15)	(0.15)
$BUS1Y1Y^{\text{prelim}}$	0.88***	0.92***	0.93***	0.90***	0.98***	0.98***
	(0.04)	(0.06)	(0.06)	(0.06)	(0.08)	(0.08)
$BUS5Y^{\text{prelim}}$				−0.01	−0.10	−0.10
				(0.08)	(0.13)	(0.13)
$PAGO^{\text{prelim}}$	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, $PAGO_t^{\text{prelim}}$ 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 C.4: Estimates for the predictive model for the forward-looking variables – *continued*

(c) BUSL as dependent variable

	$BUS5Y^{\text{np}}$	$BUS5Y^{\text{pa}}$	$BUS5Y^{\text{pa}}$	$BUS5Y^{\text{np}}$	$BUS5Y^{\text{pa}}$	$BUS5Y^{\text{pa}}$
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)
$PEXP^{\text{prelim}}$				0.21*	0.39**	0.40**
				(0.12)	(0.16)	(0.16)
$BUS1Y1Y^{\text{prelim}}$				0.00	0.16*	0.14
				(0.06)	(0.09)	(0.09)
$BUS5Y^{\text{prelim}}$	0.79***	0.82***	0.84***	0.74***	0.51***	0.54***
	(0.06)	(0.08)	(0.08)	(0.08)	(0.13)	(0.14)
$PAGO^{\text{prelim}}$	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 C.5: Estimates for predictive models for the prelim values of the ICS variables

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

	$PAGO_t^{\text{prelim}}$	$PEXP_t^{\text{prelim}}$	$BUS1Y1Y_t^{\text{prelim}}$	$BUS5Y_t^{\text{prelim}}$
Intercept	8.60	22.00***	−11.85	−7.83
	(6.21)	(5.05)	(10.29)	(7.88)
$PAGO_{t-1}^{\text{final}}$	0.78***	0.05	0.17**	0.09*
	(0.04)	(0.04)	(0.07)	(0.06)
$PEXP_{t-1}^{\text{final}}$	0.03	0.72***	0.07	0.16*
	(0.07)	(0.06)	(0.12)	(0.09)
$BUS1Y1Y_{t-1}^{\text{final}}$	0.13***	0.05*	0.82***	0.01
	(0.03)	(0.03)	(0.06)	(0.04)
$BUS5Y_{t-1}^{\text{final}}$	−0.02	0.01	0.03	0.75***
	(0.05)	(0.04)	(0.08)	(0.06)
R^2	0.87	0.76	0.86	0.79
	Covariances			
$PAGO_t^{\text{prelim}}$	43.37	12.67	23.72	13.88
$PEXP_t^{\text{prelim}}$	12.67	28.72	21.34	12.70
$BUS1Y1Y_t^{\text{prelim}}$	23.72	21.34	119.09	62.06
$BUS5Y_t^{\text{prelim}}$	13.88	12.70	62.06	69.85

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

	$PAGO_t^{\text{prelim}}$	$PEXP_t^{\text{prelim}}$	$BUS1Y1Y_t^{\text{prelim}}$	$BUS5Y_t^{\text{prelim}}$
Intercept	7.30	17.46***	−2.89	−5.69
	(6.80)	(5.49)	(11.21)	(8.46)
$PAGO_{t-1}^{\text{final}}$	0.82***	0.03	0.10	0.07
	(0.05)	(0.04)	(0.08)	(0.06)
$PEXP_{t-1}^{\text{final}}$	0.02	0.72***	−0.02	0.18
	(0.09)	(0.07)	(0.15)	(0.11)
$BUS1Y1Y_{t-1}^{\text{final}}$	0.12**	0.00	0.81***	0.03
	(0.05)	(0.04)	(0.08)	(0.06)
$BUS5Y_{t-1}^{\text{final}}$	−0.04	0.13**	0.14	0.73***
	(0.08)	(0.06)	(0.13)	(0.10)
R^2	0.87	0.79	0.84	0.79
	Covariances			
$PAGO_t^{\text{prelim}}$	43.12	15.25	31.13	19.81
$PEXP_t^{\text{prelim}}$	15.25	28.16	28.77	20.92
$BUS1Y1Y_t^{\text{prelim}}$	31.13	28.77	117.42	64.19
$BUS5Y_t^{\text{prelim}}$	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).