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Andreas Orland and Michael W.M. Roos[1]

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Abstract

We experimentally test the price-setting behavior of firms in the Rotemberg (1982) model in order to explain puzzles in the New Keynesian Phillips curve (NKPC). By constructing categories and a quantitative measure that compare behavior with optimum we find heterogeneous price-setting behavior by degree of information acquired about the future. Subjects rarely use past information, but overweight their own past price. We study the impact of heterogeneous price-setting behavior on estimated theoretically derived and hybrid Phillips curves. We find support for features of both NKPCs in our findings at the micro level. But the hybrid NKPC has a superior fit.

JEL Classification: C91, D92, E52

Keywords: Hybrid Phillips curve; experimental economics; behavioral macroeconomics

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1 Introduction

Monetary policy's effect on output is due to the New Keynesian Phillips curve (NKPC). Modern macroeconomic models are microfounded and derive the NKPC from firms that face frictions when setting prices. The NKPC derived from theoretical models is forward-looking in the sense that current inflation depends on expected future inflation but not on past inflation as older versions of the Phillips curve do. In particular, theory predicts that expected future inflation enters the Phillips curve with a coefficient of one (or very close to one if there is discounting). In empirical studies, however, the estimated coefficient of expected inflation is often much smaller than one (e.g. Fuhrer, 1997; Galí and Gertler, 1999; Rudd and Whelan, 2005; Lindé, 2005; Schorfheide, 2008) and inflation is persistent which led to the so-called hybrid version of the NKPC. The hybrid version has weak theoretical foundations but seems to fit the data better than the pure version. In our reading of the literature there seems to be evidence that both future and past inflation do matter but their relative weights are unclear. This unsatisfactory result may be due to econometric difficulties which are heavily discussed in the literature as well (see Galí et al., 2005; Dufour et al. 2006; Nason and Smith, 2008; Hall et al., 2009).

The size of the weights of past and expected future inflation in the NKPC is an important question since they determine the responses of inflation to monetary and other shocks. If the Phillips curve is purely forward-looking, it predicts disinflationary booms which are in contrast to commonly held views about the effects of monetary policy as argued by Ball (1995) and Mankiw (2001). The purely backward-looking Phillips curve also has implausible properties as it predicts oscillatory dynamics. The hybrid NKPC predicts a boom in the first periods after a contractionary monetary shock that turns into a bust in later periods. The average effect of monetary policy is zero (Mankiw, 2001).

A related important question is then *why* the empirically estimated Phillips curves seem to differ from the purely forward-looking theoretical one. The lagged inflation term in the hybrid Phillips curve is an ad-hoc modification to provide a better fit to the data, but has little theoretical justification. Indexation can be a reason why agents do not look into the future to make decisions, but stick to current information (e.g. Barro, 2001; Gray, 1978; Christiano et al., 2005). Similarly, it is hard to explain why the weight on expected future inflation term should not receive full weight.

In the first chapter of this dissertation, we test the microfoundations as proposed by Calvo (1983) experimentally. We rarely observe backward-looking behavior. About half of the subjects set optimal prices while about a third is myopic. When we estimate Phillips curves with the experimental data, we find weights on past and future expected inflation that are in line with empirical data. Thus, we offer myopia of some agents as a theoretical explanation for the puzzle of too little weight on future expected inflation.

Another popular model to derive the NKPC is by Rotemberg (1982). In the Rotemberg model a representative firm faces a cost for changing its price over time (in addition to a loss due to deviating from a desired price that it would set in absence of the price-changing costs). These menu costs are usually justified by some kind of "consumer anger", where price changes are punished by the customers of the firm. Depending on the relative size of the menu costs the firm has to smooth its set prices by deviating from desired prices. In this paper we test the Rotemberg model of price-setting frictions and implement it in a laboratory experiment. In the experiment we observe how subjects set prices in a Rotemberg situation and test whether their behavior can be described by full intertemporal optimization which on aggregate leads to the theoretical Phillips curve. On the other hand, if the subjects' behavior deviates from this benchmark, a different NKPC results. We examine actual behavior and discuss the consequences for the NKPC.

Even though the intuition of the Rotemberg model is simple, the theoretical solution is not. One possible explanation for deviations from optimal behavior in complex decisions is that subjects use heuristics. The idea that agents use rules of thumb when making intertemporal decisions is well established in macroeconomics (see Campbell and Mankiw, 1991; Krusell and Smith, 1996). Our previous findings on the work with the Calvo model suggest that myopic behavior might play a role in the price-setting behavior of subjects and we examine whether this is also the case in the Rotemberg model and discuss the consequences for the Phillips curve.

In a lab experiment it is possible to implement the stylized Rotemberg setting in a way that allows us to test the theory very directly and to observe otherwise unobservable variables. This is a clear advantage over econometric work with field data. Field data has also the downside that the real world is in a constant flow where institutions and important policy variables and information sets change over time. Laboratory experiments give us control over otherwise changing parameters, so we can isolate effects of a change of variables in different treatments.

2 Theory and Research Questions

Rotemberg (1982) formulates a dynamic model with an infinite time horizon in which price adjustment for a monopolist is costly. In this model a representative firm faces the problem to set prices z. In each period the firm can set a new price. There is a desired price p^* in each period and the firm wants to deviate as little as possible from it. The maximum achievable profit of the firm is reduced by two components: (i) losses due to the fact that the firm deviates with its set price from the desired price of the same period, and (ii) adjustment costs from changing its price over time (menu costs). Both deviations enter the loss function squared. The following equation shows the optimization problem of the firm:

$$\min_{\{z_t\}_{t=0}^{\infty}} E_t \sum_{k=0}^{\infty} \beta^k [(z_{t+k} - p_{t+k}^*)^2 + c(z_{t+k} - z_{t+k-1})^2] \tag{1}$$

The parameter c in this minimization problem measures the relative weight of the adjustment costs and $\beta = \frac{1}{1+\rho}$ is the firm's discount factor (with the time preference rate ρ).

After solving the FOC of the problem, this second-order difference equation describes the solution:

$$z_{t+1} - \left[1 + (1+\rho)\frac{1+c}{c}\right] z_t + (1+\rho) z_{t-1} = -\frac{1+\rho}{c} p_t^* \tag{2}$$

Assuming an initial and a terminal boundary condition, the solution for this problem is (Kennan, 1979; Rotemberg, 1987):

$$z_t^* = \lambda_1 z_{t-1} + (1-\lambda_1)[\frac{\lambda_2 - 1}{\lambda_2} \sum_{k=0}^{\infty} (\frac{1}{\lambda_2})^k \, p_{t+k}^*] \tag{3}$$

where $0 < \lambda_1 < 1$ and $\lambda_2 > 1$ are the stable and unstable characteristic roots of the difference equation in Equation (2).

Equation (3) gives the optimal price z_t^* of the firm. It depends on the weighted realizations of one past set price, the current and all expected future desired prices.

With a few additional assumptions (see e.g. Roberts, 1995, or Ireland, 2007), Rotemberg's model implies the New Keynesian Phillips curve:

$$\pi_t = \beta \, E_t \pi_{t+1} + \gamma \tilde{y}_t, \tag{4}$$

where $\tilde{y}_t$ is the output gap and γ its relative weight. The crucial feature in this Phillips curve is that current inflation depends on currently expected *future* inflation $E_t\pi_{t+1}$. In contrast, the hybrid version also contains a lagged term and the weight on $E_t\pi_{t+1}$is typically less than predicted:

$$\pi_t = \beta^f E_t\pi_{t+1} + \beta^b\pi_{t-1} + \gamma\tilde{y}_t \; with \; 0 < \beta^f, \beta^b \leq 1. \tag{5}$$

Schorfheide (2008) surveys the empirical literature of DSGE-model based estimations of the coefficients. The coefficients on lagged inflation range between 0 and .72 , the coefficients on future inflation between 0 and 1, depending on estimation method, sample period and proxy for the output gap used.

Given that empirical work consistently found smaller weights on future inflation than predicted by theory, we examine the causes of this puzzle experimentally on the micro level. We implement the Rotemberg model into the lab to answer the following questions:

1) Are subjects on aggregate able to set prices predicted by the model? Do they *systematically* deviate from the optimal prices? Do they either smooth too much or not enough when they set prices? In theory, all information is available freely and without effort. When we change this and bring our model closer to reality, do the results change? When subjects have to acquire information about future periods (at no monetary cost), we can observe what and how much information subjects use and we can answer the question if more informed subjects set different prices than the less informed subjects.
2) The theoretical solution (in Equation (3)) can be understood as a weighting scheme to be applied on one own set price and current and future desired prices. Do subjects (that decided to acquire different degrees of information) behave according to that

scheme? Do we find backward-looking behavior when we extend estimations by a-theoretical past desired prices or set prices farther away than one period.

3) What are the consequences of our findings above for the New Keynesian Phillips curve? Can we explain the empirical observations of a too small weight on future expected inflation with the observed behavior of the firms in our experiments? Can we find a positive weight on past inflation and explain it by observed firm behavior? To achieve that we estimate both theoretically derived and hybrid Phillips curves.

3 Experimental Design

We implement the model as closely as possible in the laboratory by generating a Rotemberg situation. The experiment is framed in neutral terms with "prices" being called "values", but we use the price-setting terminology here for the ease of the exposition. We use z-Tree by Fischbacher (2007) to conduct the experiments computerized.

Table 1: Summary of the treatments

	Free Information	Information for Effort
Stationary Time Series/ High Cost (c=3)		Treatment 4 (18)[0]
Stationary Time Series/ Low Cost (c=0.5)		Treatment 3 (31)[0]
Non-stationary Time Series (c=20)	Treatment 1 (38)[1]	Treatment 2 (38)[5]

Notes: Free Information/Information for Effort refers to the availability of the desired prices.

The number of participants is shown in brackets, in square brackets the number of subjects that exceeded the loss limit..

To answer our research questions, we design four treatments where we vary the price setting cost via the parameter c, the availability of information about the desired prices and the time series of desired prices. The experimental design is displayed in Table 1.[2] To keep the experiment as simple as possible, we abstract from discounting (so $\rho = 0$ in all treatments). Notice also that we do not need to be concerned about expectation formation as there is no uncertainty about desired prices: $E_t p^*_{t+j} = p^*_{t+j}$. Usually the desired prices stem from the price level in the overall economy *and* the output gap. Again for simplicity, we decided to supply subjects only with desired prices and abstract from output gaps.

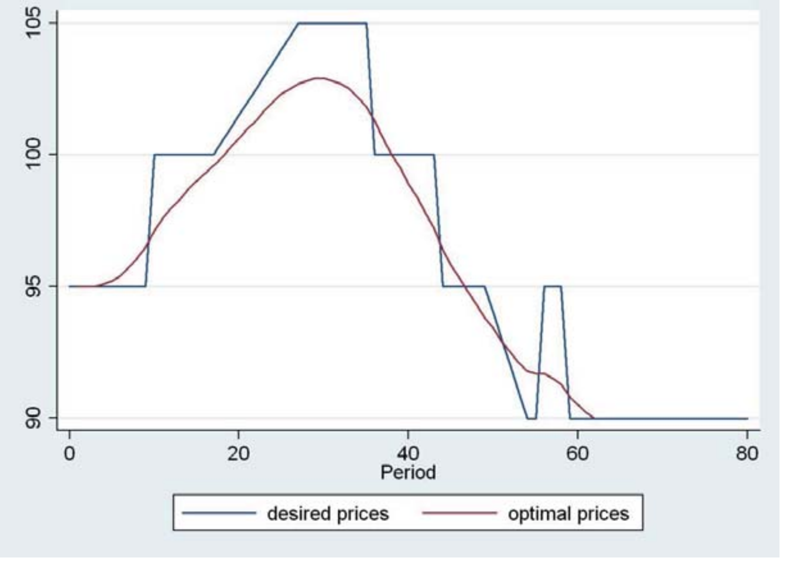
In the treatments with the non-stationary time series, treatments 1 and 2, we chose a parameter *c=20.* Treatments 1 and 2 differ with respect to the availability of information. In treatment 1, all information about the future is available at once from the beginning. In treatment 2, it takes effort to acquire information. Buttons cover the information about future periods' desired prices and subjects have to decide whether and how many periods to uncover by clicking the buttons. Acquiring information in these treatments is associated with cognitive costs, but not with monetary costs. Screenshots of the participants' z-Tree computer screen are shown in Figure A1 (Free Information treatment) and Figure A2 (Information for Effort) in the appendix.

Figure 1 displays the desired prices p^*_t and optimal prices z^*_t (optimal prices are only shown in Figure 1 for the periods that the experiment actually lasted, see following explanation about the terminal boundary condition). The figure shows nicely how subjects have to smooth with their set prices in order to minimize costs and losses. In

[2] We also conducted a treatment were subjects were equipped with two on-screen calculators that displayed the cost or loss that subjects would incur in the current period for any price entered in a designated field. Subjects could try different prices and study the consequences for losses and costs with the calculator before finally setting a price. We do not use the data of this treatment for this paper as it does not fit to the research questions posed here.

our work with the Calvo (1983) model we used stationary time series with and without trend and we wanted to test the Rotemberg model with both stationary and non-stationary time series in this paper. The difference between treatment 1 and 2 is how information about future desired prices is supplied. Treatment 1 is closer to the usual assumption of economic theory that economic agents have all information available at no cost (neither monetary nor cognitive). Treatment 2 brings the model closer to reality where information acquisition is usually at least costly in the sense that economic agents have to decide if and how much information they want to acquire. When we compare aggregate behavior of treatment 1 and 2, we can see if our variation in treatment 2 influences the way subjects set prices.

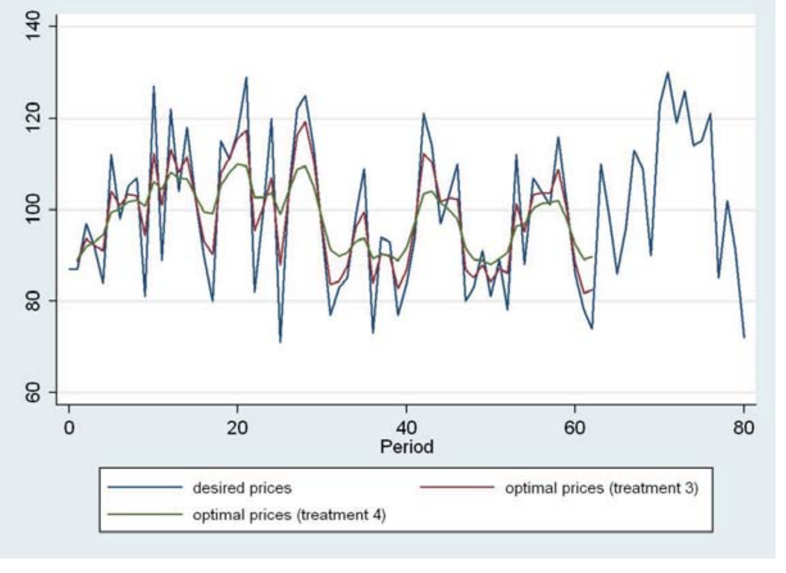
Figure 1: Desired and optimal prices in treatments 1 and 2



In treatments 3 and 4, we use a stationary time series. In both treatments information has to be acquired by clicking buttons, as indicated above. We varied the cost parameter c between treatment 3 ($c = 0.5$) and 4 ($c = 3$).

Figure 2 displays the desired prices p_t^* and optimal prices z_t^* in treatments 3 and 4. In both treatments we used same time series of desired prices. The time series consists of random draws from a uniform distribution on [70; 130] and is identical to the one in the previous chapter, though cut off after period 80. Due to the different cost parameters the optimal solutions differ: in treatment 3 (with $c = 0.5$) subjects have to smooth less and can seek more orientation in the current desired price than in treatment 4 (where $c = 3$).

Figure 2: Desired prices and optimal prices in treatments 3 and 4

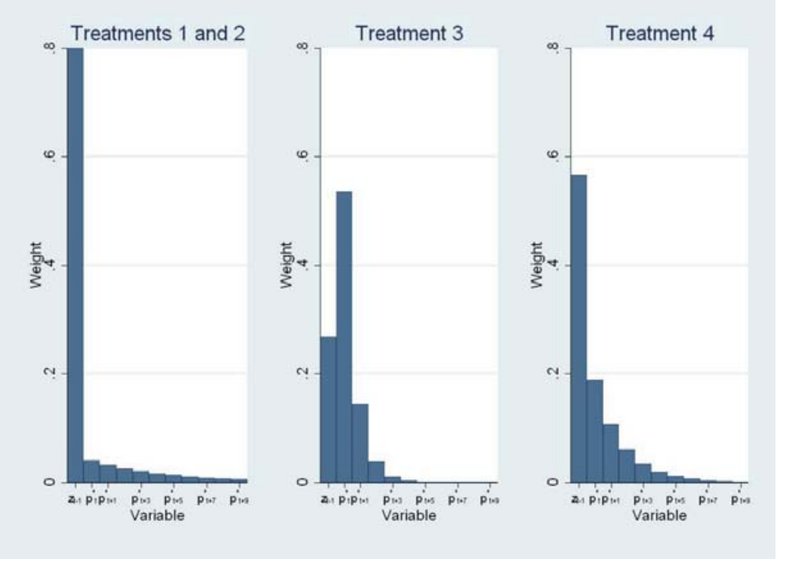


In treatments 3 and 4 the desired prices are more volatile than in treatments 1 and 2,[3] hence the lower cost parameters in these treatments.[4] We chose to conduct treatments 3 and 4 because the more volatile stationary time series requires subjects to adjust the prices they set more strongly and hence makes the experiment a more demanding task.

[3] Standard deviation of desired prices is 15.84 in treatments 3 and 4 and 5.37 in treatments 3 and 4.
[4] A cost parameter $c = 20$ implies a series of optimal prices that resembles very much a flat line with the stationary time series. We opted for the smaller parameters instead to induce subjects to change their prices over time.

Another reason to conduct these treatments is to examine if subjects behave according to the optimal solution when quite different weighting schemes are implied for treatment 3 and 4. Figure 3 displays the weights predicted by theory. The weighting scheme of treatment 3 has the mode at the current desired price, treatment 4 at the own past set price. In treatment 3 subjects have to consider future information more than in treatment 4.

Figure 3: Weights on past set price and current and future desired prices for all treatments



The experiment is an individual choice task in which subjects are paid according to their accumulated period profits over the whole experiment. We only told the subjects in the instruction that their task was to set values and that their earnings would be determined by their decisions. The profit per period was given as

$$\text{Profit of the period} = \text{Maximum Profit} - \text{Loss of the period} - \text{Cost of the period} \qquad (6)$$

with the loss function

$$\text{Loss of the period} = [\text{Set price of the period} - \text{Desired price of the period}]^2 \quad (7)$$

and the cost function

$$\text{Cost of the period} = c * [\text{new set price} - \text{old set price}]^2 \quad (8)$$

The calibration for the different treatments is summarized in Table 2. We calibrated all treatments so that optimal behavior attained around 30 euros (not including show-up). The experimental currency was called points and converted into euros at payoff.

Table 2: Calibration of the different treatments

	Treatments 1 and 2	*Treatment 3*	*Treatment 4*
Cost parameter *c*	20	0.5	3
Maximum profit per period (points)	43	400	400
Loss limit (points)	3,440	32,000	32,000
Exchange rate (points/euro)	75	750	600
Optimal payoff (in euros without show-up)	30.74	29.99	29.12
Show-up fee (in euros)	4.00	4.00	4.00

Subjects were presented in each period either a table with all 80 periods' desired prices displayed (Free Information treatment 1) or with all future desired prices covered by buttons (Information for Effort treatments 2, 3 and 4). Subjects had to decide in these treatments if and how many future periods' desired prices to uncover (while current and past desired prices were shown without effort). In all treatments the current desired price was marked in a different color than the other periods' prices.

Subjects were supplied on-screen with the Windows calculator that they had to activate. A history table at the bottom of the screen summarized all information about past periods (desired and set price of each period, whether a new price was set or not, loss, cost, earnings and total earnings until this period). In the center of the screen subjects had to enter a price to set (in the range between 0 and 200) and to click on an OK button in order to proceed to the next period.

Due to the quadratic loss and cost function subjects could incur very high negative period profits. As we wanted to ensure incentive compatibility throughout the experiment, we introduced a loss limit. Once a subject exceeded the loss limit he or she had to leave the experiment and received only the show-up fee. The loss limit was set in each treatment to the maximum profit that subjects could achieve during the maximum number of 80 periods in the experiment.[5]

The theoretical solution assumes an initial and a terminal boundary condition. We deal with the initial condition by supplying subjects at the very start of the experiment with a set price equal to the desired price of the first period. The terminal condition is introduced the following way: It was announced in the instructions that the experiment would last between 60 and 80 periods and that the actual end of the experiment had been determined by a random device beforehand. The randomly determined end period was in period 62 for all subjects.

We invited subjects to our lab in Ruhr University Bochum, RUBex. Each session lasted about 120 minutes. The procedure in the laboratory was the following: we played a pre-recorded audio version of the instructions while each subject also had a paper copy that he/she could use during the experiment. In the instructions, we did not supply a formula for the optimal values (z_t^*), but explained subjects the cost structure of the experiment as given in Equations (6)-(8). Control questions were distributed and the subjects had to answer all questions correctly before the experiment started. We let them play five non-incentivized trial periods before the incentivized part of the experiment in order to make the participants familiar with the user interface. After all participants had

[5] Five of the six subjects that had to leave the experiment (see Table 1) presumably made a typo in the experiment that was so large that they exceeded the loss limit even though they had accumulated some profits in the periods previous to the typo. The other subject made big price jumps for seven periods before he exceeded the loss limit.

concluded the trial periods, the incentivized part started. After the 62 incentivized periods all participants filled out a questionnaire that asked for personal details. Then subjects received their payoffs privately and in cash. Average payoff of all subjects was 24.99 euros.[6]

4 Results

In the following sections we only consider the behavior of subjects that completed the whole experiment. Subjects that exceeded the loss limit and left the experiment are not included in the following analyses. As already mentioned, in most of the cases subjects obviously made very huge mistakes due to typos when entering their prices. We do not want these typos to drive our results as we only have a low number of observations in comparison to other studies that examine price-setting at the micro level with survey or scanner data.

Table 3 supplies summary statistics of all four treatments. In treatment 1 subjects earned about 70% of the profits in optimum. Though information had to be uncovered in treatment 2, subjects on average earned about 72%. Subjects on average earned less in treatment 4 than in treatment 3 (75% in contrast to 83% of optimal profits.

In only about 2% of the periods subjects decided to use the calculator in treatments 1 and 2. In treatments 3 and 4 this share is four to five times higher. When looking at Figures 1 and 2, price setting in the treatments with the non-stationary time series seems more intuitive. So the higher share of calculator usage can be explained by subjects facing the more demanding task.

[6] When receiving their payoffs, subjects had to hand in the instructions. Some of the subjects' instruction sheets had notes on them but no subject wrote down the time series.

Table 3: Summary statistics for the different treatments

	Treatment 1	*Treatment 2*	*Treatment 3*	*Treatment 4*
Profit per period	25.89	26.67	263.23	182.74
	(72.52)	(48.33)	(233.98)	(247.36)
Optimal profit	37.19	37.19	314.38	243.06
Loss per period	4.44	6.55	72.90	149.84
	(10.24)	(13.82)	(171.37)	(188.53)
Optimal loss	2.90	2.90	45.41	124.40
Cost per period	12.66	9.77	63.87	67.41
	(71.60)	(46.74)	(133.29)	(149.30)
Optimal cost	2.91	2.91	40.21	32.54
Share calculator used	.02	.02	.08	.10
	(.14)	(.14)	(.27)	(.30)
Time (sec)	16.63	22.12	33.86	36.43
	(15.94)	(39.77)	(33.83)	(46.69)
# subjects	37	33	31	18

Note: Standard deviations in parentheses.

In the Information for Effort treatments, treatments 2, 3 and 4, we observe how many periods' future desired prices were uncovered in each period t by each subject i, we call the variable $PU_{i,t}$.[7] To construct categories for the subjects we use the following measure, the mean number of periods uncovered by each subject i, MPU_i:

$$MPU_i = (\sum_{j=1}^{62} PU_{i,j})/62 \qquad (9)$$

Table 4 provides an overview about the number of periods each subjects uncovered in Column (1). The subjects use different amounts of information about the future in the effort treatments. On average each subject clicked between 2.85 (treatment 3) and 3.67 buttons (treatment 2) in each period. In Treatment 2 with a much higher cost parameter than in treatments 3 and 4, subjects on average look up more information.

[7] We only consider the *amount* of information looked up by participants, not *which* future period's information they looked up when they did it. We looked at the data and found that subjects almost always looked into the near future (in contrast to e.g. randomly selected information or information farther away). Hence we conclude that the assumption that more information means more relevant information about the near future is justified.

Table 4: Mean number of periods uncovered by treatment and information category

	All subjects without dropouts	*Very Uninformed Subjects*	*Relatively Uninformed Subjects*	*Relatively Informed Subjects*	*Very Informed Subjects*
	(1)	(2)	(3)	(4)	(5)
Treatment 2	3.67	.97	2.95	4.45	6.30
	(2.18)	(.88)	(.36)	(.35)	(1.74)
	[0; 10.37]	[0; 2.19]	[2.52; 3.63]	[3.82; 4.92]	[4.97; 10.37]
Treatment 3	2.85	.97	2.14	3.22	5.28
	(1.63)	(.85)	(.17)	(.23)	(.76)
	[0; 6.47]	[0; 1.87]	[1.95; 2.47]	[2.98; 3.69]	[4.50; 6.47]
Treatment 4	2.87	.15	1.60	4.10	5.58
	(2.19)	(.27)	(.39)	(.53)	(.18)
	[0; 5.79]	[0; .55]	[1.27; 2.11]	[3.40; 4.56]	[5.35; 5.79]

Notes: Standard deviations in parentheses. Minimum and maximum in square brackets.

We create four equally sized groups to analyze how information acquisition affects price-setting behavior by applying the quartile criterion. We label the groups “very uninformed”, “relatively uninformed”, “relatively informed” and “very informed subjects”. Columns (2)-(5) display the mean MPU of the groups. We see that subjects in the four groups decided quite differently how much information to acquire: the means in each treatment increase strongly by information quartile. In the following sections we cover the question how the degree of information that the subjects decided to acquire relates to behavior in the groups and on an aggregate level. Table A1 in the appendix shows that more informed subjects earned significantly more in treatments 2 and treatment 4. We see this as a first indication that more informed subjects behaved differently than less informed subjects in these treatments. However, we cannot find this in treatment 3, the treatment with the lowest price adjustment parameter c. Though the groups in this treatment did not earn significantly different profits, this does not necessarily mean that there is no difference in behavior. Different behavior across information categories simply might have not translated into significantly different payoffs.

4.1 Deviations from Optimum

In a first step, we examine the impact of information acquisition on deviations of price-setting behavior from optimum. As can be seen in Equation (3), the optimal price in each period depends not only on the current and future desired prices but also on the own price set in the previous period. We control for the deviation from the optimal price in the previous period by introducing a conditional optimal price $z^*_{t|z_{t-1}}$. We define it by:

$$z^*_{t|z_{t-1}} = \lambda_1 z_{t-1} + (1-\lambda_1)\left[\frac{\lambda_2 - 1}{\lambda_2}\sum_{k=0}^{18}\left(\frac{1}{\lambda_2}\right)^k p^*_{t+k}\right] \tag{10}$$

Only very little weight is on the desired prices farther away than 18 periods in the future.[8] This ensures that we make a neglectably small error by deviating with our conditional optimal price $z^*_{t|z_{t-1}}$ from the (unconditional) optimal price z^*_t even in case that the past set price z_{t-1} is identical to the past optimal price z^*_{t-1}. On the other hand, we gain the advantage that the conditional optimal price allows us to examine each period's price setting individually because deviations of past set prices from the (unconditional) optimal price of that period do not influence current price setting.

We then create five categories that describe the set price in any given period in comparison with the conditional optimal price and the desired price of the period. Our

[8] In treatments 1 and 2, our definition of the conditional optimal price has 99.71% of the weight, in treatments 3 and 4 almost 100%. By using 18 leads we also exploit our data efficiently: we can use all our observations of set prices. Even for the last observations of set prices in period 62 we still have all 18 leads of future desired prices.

classification makes it necessary to distinguish situations when the desired price is either higher or lower than the conditional optimal price. We call the former booms and the latter busts.

Figure 4: Illustration of the behavioral categories in the case of a bust

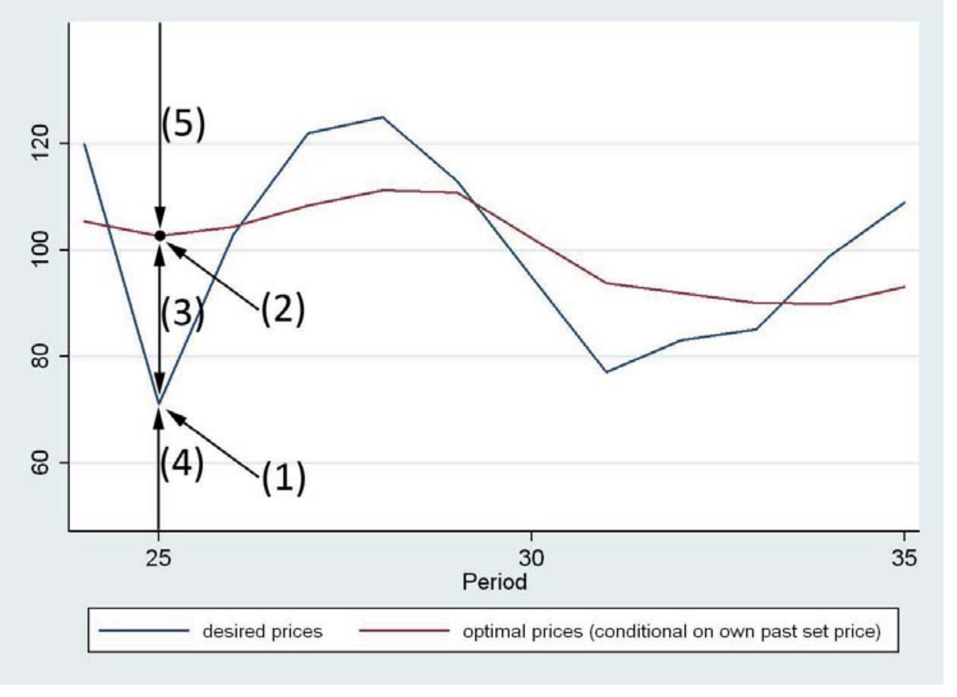


Figure 4 displays the five categories exemplarily in the case of the bust in period 25. The point marked with (1) describes a set price that equals exactly the desired price. We call this "no smoothing" as the subject does not optimize between loss and cost component. Optimal behavior is displayed as a dot, a small range, marked with (2). It is very difficult to set exactly an optimal price. Therefore we define optimal behavior as a range of ±0.25% around the conditional optimal price.[9] The range marked with (3) depicts set prices between our definitions of optimal behavior and no smoothing. Here the firm

[9] This decision is discretionary. We tried other ranges which did not change our results qualitatively. Therefore we decided that the strict definition with a small range around the conditional optimal price serves the purpose of our analysis.

smoothes, but not enough, hence we call it “some smoothing”. We call the interval where the set price is (in a bust) below the desired price, (4), “too extreme”. Finally, (5) characterizes the range of set prices that are (in a bust) above the conditional optimal price. We call this “too much smoothing”. The categories for booms are defined analogously. Table 5 summarizes the categories in both booms and busts.

Table 5: Behavioral categories by economic cycle

Economic situation	Subject’s behavior	Category
Boom: $p^*_{i,t} > z^*_{i,t\|z_{i,t-1}}$	$z_{i,t} > p^*_{i,t}$	Too extreme
	$z_{i,t} = p^*_{i,t}$	No smoothing
	$z_{i,t} > 1.0025\ z^*_{i,t\|z_{i,t-1}}$	Some smoothing
	$1.0025\ z^*_{i,t\|z_{i,t-1}} \geq z_{i,t} \geq .9975\ z^*_{i,t\|z_{i,t-1}}$	Optimal behavior
	$z_{i,t} < .9975\ z^*_{i,t\|z_{i,t-1}}$	Too much smoothing
Bust: $z^*_{i,t\|z_{i,t-1}} > p^*_{i,t}$	$z_{i,t} > 1.0025\ z^*_{i,t\|z_{i,t-1}}$	Too much smoothing
	$1.0025\ z^*_{i,t\|z_{i,t-1}} \leq z_t \leq .9975\ z^*_{i,t\|z_{i,t-1}}$	Optimal behavior
	$z_{i,t} < .9975\ z^*_{i,t\|z_{i,t-1}}$	Some smoothing
	$z_{i,t} = p^*_{i,t}$	No smoothing
	$z_{i,t} < p^*_{i,t}$	Too extreme

The categories describe price-setting behavior and give an impression about the Phillips curve. When subjects set prices that are optimal, they are in line with theory and the theoretically derived Phillips curve emerges. Observed behavior that does not fall in our range of optimal behavior thus changes the Phillips curve. When firms smooth more than predicted with their prices, they behave as if the price adjustment parameter c is higher than it actually is. The effect on the coefficient of expected future inflation in the NKPC is that it will become larger than predicted. On the other hand do the other three categories (some smoothing, no smoothing and too extreme) describe prices that do not smooth enough given the economic environment. A firm that sets prices in the ranges of these categories behaves as if the cost parameter c is smaller than it actually is. The consequence for the Phillips curve is that the coefficient on future expected inflation is smaller than predicted (where the impact of "some smoothing" is smaller than "too extreme").

Using the categories we turn to the question how information acquisition relates to behavior. We hypothesize that more informed subjects exhibit more optimal behavior and are less likely to set none-smoothing and extreme prices. According the other two categories, "too much smoothing" and "some smoothing", we do not have expectations how more or less information relates to them.

Table 6: Correlation of subjects' average information acquisition per period with behavioral category

		Spearman's rank correlation coefficient		
		Boom& bust periods (1)	*Boom periods* (2)	*Bust periods* (3)
Category of Behavior	Too much Smoothing	.03*	0.00	.07**
	Optimal behavior	.12**	.15**	.06*
	Some smoothing	-.09**	-.11**	-.07**
	No smoothing	-.03*	-.03	-.03*
	Too extreme	-.04**	-.02	-.09**

Note: ** indicates significance level of 1%, * of 5% significance level.

We calculate the Spearman correlation coefficients of the mean periods that a subject uncovered per period (MPU_i) with dummy variables for the behavioral categories.[10] In Column (1) of Table 6, the coefficients for both booms and busts are shown, Columns (2) and (3) display them separately for booms and busts. In both booms and busts together

[10] The correlation coefficients of $PU_{i,t}$ with dummy variables for the behavioral categories show essentially the same results. But as we further on work with the four categories of the subjects, we focus on MPU_i.

more informed subjects act significantly more often optimal, as hypothesized. They also behave less often optimizing and too extreme. We take this as first evidence that subjects set different prices, depending on how much information they acquired.[11]

Table 7 summarizes the set prices in a contingency table across information and behavioral categories in treatments 2, 3 and 4 together (as the three treatments show similar properties). We see that oversmoothing is the most frequent category and that set prices fall more often in that category when subjects acquire more information. About 18% of all prices set fall in the category of optimal behavior. Given the small range that defines this category, still many prices fall in it. As with oversmoothing, more informed subjects set optimal prices more often. In contrast to that, the remaining three categories' share in total behavior decreases with information. The behavior in booms and busts is similar and shown separately in Tables A2 and A3 in the appendix.

Table 7: Behavioral categories by information categories in treatments 2, 3 and 4

		Information Acquisition				Total
		Very Uninformed Subjects	*Relatively Uninformed Subjects*	*Relatively Informed Subjects*	*Very Informed Subjects*	
Category of Behavior	Too much Smoothing	369 (31.32%)	422 (35.82%)	390 (33.11%)	497 (42.19%)	1,678 (35.61%)
	Optimal behavior	157 (13.33%)	206 (17.49%)	247 (20.97%)	221 (18.76%)	831 (17.64%)
	Some smoothing	269 (22.84%)	264 (22.41%)	238 (20.20%)	210 (17.83%)	981 (20.82%)
	No smoothing	311 (26.40%)	249 (21.14%)	243 (20.63%)	207 (17.57%)	1,010 (21.43%)
	Too extreme	72 (6.11%)	37 (3.14%)	60 (5.09%)	43 (3.65%)	212 (4.50%)
Total		1,178 (100%)	1,178 (100%)	1,178 (100%)	1,178 (100%)	4,712 (100%)

Note: Column percentages in brackets

[11] To explore potentially asymmetric behavior in booms and busts is beyond the scope of this paper.

The categories do not show how strong the set price deviates from the conditional optimal price. To examine the deviation quantitatively, we introduce a measure for the distance of the set price from the conditional optimal price:

$$\text{Distance}_{i,t} = \begin{cases} z^*_{i,t|z_{i,t-1}} - z_{i,t} \text{ if } p^*_{i,t} > z^*_{i,t|z_{i,t-1}} \\ z_{i,t} - z^*_{i,t|z_{i,t-1}} \text{ if } p^*_t < z^*_{i,t|z_{i,t-1}} \end{cases} \qquad (11)$$

In case of optimal behavior (conditional on past behavior), this measure takes the value zero. It takes positive values for set prices that oversmooth and negative values for too few smoothing. They larger (smaller) the value is the more oversmoothes (undersmoothes) the subject with the set price (measured in points).

Table 8 shows the mean distances for all treatments and across information categories in the treatments. In all treatments on average subjects undersmooth slightly (remember that this means a smaller coefficient on expected future inflation than theoretically predicted in the resulting NKPC). When we look at the mean distances across information categories, we see that the least informed subjects undersmooth strongly. In the more informed categories subjects set prices that are closer to optimum. Finally, in treatments 2, 3 and 4 the very informed subjects on average smooth slightly too much. This finding is confirmed by the Jonckhere-Terpstra test, a test for an ordered alternative hypothesis. Also correlations between distance and (mean) uncovered information have significant negative coefficients ($\rho_{\text{Distance}_{i,t},\, PU_{i,t}} = -.0302$, p=.0325 and $\rho_{\text{Distance}_{i,t},\, MPU_i} = -.0486$, p=.0005).

Even though we did not observe significant differences of profits between the four information categories in treatment 3, we see in Table 8 clearly how the distance of the set prices to the optimal prices decreases with information acquired. Hence behavior in all treatments is strongly related to information acquisition. We conclude that in all treatments the more informed set prices closer to predictions whereas the less informed set prices that do not smooth enough.

Table 8: Distance of set price from conditional optimal price by treatment and information degree

	All subjects without dropouts	*Very Uninformed Subjects*	*Relatively Uninformed Subjects*	*Relatively Informed Subjects*	*Very Informed Subjects*	*Jonckhere-Terpstra test (ascending ordered alternative)*
Treatment 1	-.069 (.74)					
Treatment 2	-.024 (.71)	-.127 (.87)	.093 (.74)	-.067 (.55)	.041 (.61)	$J^* = 3.694$ p=.0001
Treatment 3	-.208 (5.08)	-1.581 (5.62)	-.438 (4.63)	-.188 (4.90)	.105 (4.49)	$J^* = 6.153$ p=.0000
Treatment 4	-.037 (3.33)	-.605 (4.43)	-.149 (2.93)	.013 (2.46)	.492 (2.81)	$J^* = 3.113$ p=.0009

Notes: Standard deviations in parentheses.

4.2 Weights on Future and Past

To examine the question whether past information matters for price-setting, we choose a different approach than in the previous section. We use Equation (3) to examine what weights subjects put on their own past set price and current and future desired prices and extend it by a-theoretical backward-looking terms. Working with deviations from the conditional optimal price in the previous section had the advantage that we could analyze behavior in each period separately but neglected the change of set prices over time. Working with the weighting scheme allows us to tackle the question how information is weighted over time.

A priori, subjects might seek information in either exogenous information, the desired prices, or endogenous information, their own set prices (beyond the first lag).

Considering desired or set prices is a-theoretical but both are plausible in a complex situation. We look at the two possibilities in the next two sections.

4.2.1 Weights on Past Desired Prices

Once the own past set price is included in the price-setting, lagged values of desired prices should not matter for the price-setting decision. Hence all past desired prices should have zero weight. Figure 3 displays the weights predicted by theory.

We use five past desired prices, one past set price, the current desired price and five future desired prices in our regression to explain the weights that determine the set prices:

$$z_{i,t} = \sum_{k=1}^{5} \alpha_k \, p^*_{i,t-k} + \beta z_{i,t-1} + \sum_{l=0}^{5} \gamma_l \, p^*_{i,t-l} + \varepsilon_{i,t} \qquad (12)$$

We estimate Equation (12) with OLS and robust standard errors and use it on the pooled data of our different treatments.[12] Then we compare the estimated weights with the theoretical predictions.

Table 9 displays the weights of all four treatments with the corresponding predictions. We see in the lower panel that the shape of the predictions is found in all treatments, though the weight on the past set price in treatments 1, 2 and 4 is higher than predicted. Weights on past desired prices are mostly small, often negative. 9 out of 20 coefficients are significantly different from zero. This raises the question whether we observe artifacts here or actual backward-looking behavior. Do optimal prices also display these small but significant coefficients on past desired prices when explained by a regression like conducted with Equation (12)? To answer this question we estimate Equation (12) with optimal prices instead of prices set by subjects:

[12] We estimated equations with up to 15 leads of the desired prices. But the theoretical weights decline quickly and we learn little from estimating them. Furthermore, the weights of the first five desired prices do not change substantially due adding more leads.

$$z_t^* = \sum_{k=1}^{5} \alpha_k \, p_{t-k}^* + \beta z_{t-1}^* + \sum_{l=1}^{5} \gamma_l \, p_{t-l}^* + \varepsilon_t \tag{13}$$

Table A4 in the appendix shows the weights of the optimal time series (again estimated with OLS and robust standard errors). We can observe that even the optimal prices exhibit artifacts similar to the ones in the estimations with observed behavior. So we assume backward-looking behavior not to be influential in observed behavior.[13]

Now we turn to the question whether there are differences in price-setting behavior across information categories. We estimate Equation (12) with the pooled data of the four information categories separately.

Table 10 shows the results for treatment 2. The coefficients do not differ much across the information categories. We observe few significant past weights and all four groups put too much weight on the set price.

Regression outputs for treatment 3 are displayed in Table 11. Only the very uninformed subjects have significant backward-looking terms. Their coefficients in the lower panel often differ from the predictions. In contrast to that, the more informed categories exhibit no significant past coefficients and only one coefficient of the relatively uninformed subjects is different from predictions. The two most informed categories have no coefficients that are different from predictions.

Finally, Table 12 shows the coefficients of treatment 4. Again, past terms are only significantly different from predictions among the very uninformed. All but the relatively uninformed put too much weight on the past set price.

[13] Some estimated weights on past optimal prices and current and future desired prices in Table A4 are significantly different from predictions. We also estimated Equation (13) with more leads of desired prices. Adding more desired prices to this regression brings coefficients of future desired prices soon very close to predictions, but past desired prices still stay significantly different from zero.

Table 9: Estimated weights implied by set prices (with lagged desired prices in upper panel) of all treatments

Dependent variable: $z_{i,t}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Treatment 1	Treatment 2	Treatment 3		Treatment 4	
	Prediction	Weight	Weight	Prediction	Weight	Prediction	Weight
$p^*_{i,t-5}$	0	.002	**-.031****	0	.005	0	-.004
		(.010)	(.001)		(.007)		(.007)
$p^*_{i,t-4}$	0	*-.027**	*.003**	0	-.006	0	.012
		(.013)	(.012)		(.007)		(.007)
$p^*_{i,t-3}$	0	-.019	-.018	0	-.015	0	-.006
		(.012)	(.012)		(.009)		(.008)
$p^*_{i,t-2}$	0	*-.031**	**-.036****	0	.014	0	**-.022****
		(.013)	(.016)		(.009)		(.007)
$p^*_{i,t-1}$	0	**-.106****	**-.084****	0	*.049**	0	.005
		(.020)	(.024)		(.027)		(.010)
$z_{i,t-1}$	.800	**.927****	**.967****	.268	*.181***	.566	**.681****
		(.016)	(.007)		(.004)		(.028)
$p^*_{i,t}$	.040	**.099****	.060*	.536	.554**	.189	.189**
		(.022)	(.023)		(.013)		(.008)
$p^*_{i,t+1}$	.032	.041*	*.064***	.144	.132**	.107	**.075****
		(.015)	(.016)		(.008)		(.007)
$p^*_{i,t+2}$	.026	.030*	.007	.038	.030**	.060	**.032****
		(.013)	(.013)		(.008)		(.006)
$p^*_{i,t+3}$	.020	.039**	.028*	.010	.011	.034	**.016***
		(.013)	(.013)		(.009)		(.006)
$p^*_{i,t+4}$	.016	.014	.016	.003	.014	.019	**.002**
		(.013)	(.011)		(.008)		(.007)
$p^*_{i,t+5}$	.013	*.032***	.024**	.001	-.000	.011	.011
		(.009)	(.007)		(.007)		(.007)
Pseudo R^2		.976	.980		.806		.796
#		2,146	1,914		1,798		1,044

Notes: * indicates t-test on difference from zero, * p<0.05, ** p<0.01, *italics* (**bold**) indicates t-test on difference of estimated coefficient from theoretical value at p<0.05 and p<0.01 respectively, robust standard errors in parentheses

Table 10: Estimated weights implied by set prices (with lagged desired prices in upper panel) across information categories in treatment 2

Dependent variable: $z_{i,t}$	(1)	(2)	(3)	(4)	(5)
	Prediction	*Very Uninformed Subjects*	*Relatively Uninformed Subjects*	*Relatively Informed Subjects*	*Very Informed Subjects*
$p^*_{i,t-5}$	0	**-.052****	**-.063****	-.002	.003
		(.019)	(.018)	(.012)	(.013)
$p^*_{i,t-4}$	0	.025	.013	-.006	-.024
		(.031)	(.023)	(.018)	(.019)
$p^*_{i,t-3}$	0	-.003	-.004	*-.044**	-.028
		(.034)	(.019)	(.019)	(.021)
$p^*_{i,t-2}$	0	-.082	-.056	-.004	-.002
		(.044)	(.040)	(.018)	(.020)
$p^*_{i,t-1}$	0	*-.145**	.038	**-.096****	*-.103**
		(.063)	(.042)	(.027)	(.043)
$z_{i,t-1}$	.800	**.951****	**.985****	**.927****	**.970****
		(.013)	(.008)	(.020)	(.013)
$p^*_{i,t}$	.040	.159*	.015	-.019	.065
		(.065)	(.020)	(.028)	(.045)
$p^*_{i,t+1}$	.032	.105*	.003	**.125****	.031
		(.046)	(.020)	(.028)	(.020)
$p^*_{i,t+2}$	.026	.010	.001	.029*	-.004
		(.029)	(.024)	(.024)	(.021)
$p^*_{i,t+3}$	.020	.008	.057*	.021	.024
		(.026)	(.025)	(.027)	(.022)
$p^*_{i,t+4}$	.016	.017	-.018	.024	.045*
		(.021)	(.024)	(.025)	(.021)
$p^*_{i,t+5}$	.013	.001	.028	*.045***	.022
		(.013)	(.016)	(.015)	(.015)
Pseudo R^2		.969	.983	.990	.982
#		464	464	464	464

Notes: * indicates t-test on difference from zero, * p<0.05, ** p<0.01, *italics* (**bold**) indicates t-test on difference of estimated coefficient from theoretical value at p<0.05 and p<0.01 respectively, robust standard errors in parentheses

Table 11: Estimated weights implied by set prices (with lagged desired prices in upper panel) across information categories in treatment 3

Dependent variable: $z_{i,t}$	(1)	(2)	(3)	(4)	(5)
	Prediction	*Very Uninformed Subjects*	*Relatively Uninformed Subjects*	*Relatively Informed Subjects*	*Very Informed Subjects*
$p^*_{i,t-5}$	0	-.001	.012	.010	-.007
		(.014)	(.014)	(.014)	(.014)
$p^*_{i,t-4}$	0	.005	-.015	-.015	.013
		(.017)	(.014)	(.014)	(.013)
$p^*_{i,t-3}$	0	.037	.018	.011	-.012
		(.019)	(.017)	(.017)	(.013)
$p^*_{i,t-2}$	0	**.060****	.015	.012	-.034
		(.017)	(.020)	(.018)	(.021)
$p^*_{i,t-1}$	0	**.244****	.047	-.006	-.019
		(.061)	(.051)	(.044)	(.029)
$z_{i,t-1}$	.268	**-.139**	.170*	.225**	.387**
		(.079)	(.085)	(.074)	(.063)
$p^*_{i,t}$	.536	**.679****	.566**	.567**	.492**
		(.023)	(.027)	(.029)	(.023)
$p^*_{i,t+1}$	.144	**.083****	.148**	.153**	.123**
		(.017)	(.017)	(.017)	(.015)
$p^*_{i,t+2}$	.038	**-.004**	.023	.030	.049**
		(.015)	(.014)	(.016)	(.013)
$p^*_{i,t+3}$	.010	.029	-.007	.013	-.002
		(.017)	(.016)	(.019)	(.016)
$p^*_{i,t+4}$	.003	-.003	*.032**	.007	.006
		(.017)	(.015)	(.015)	(.014)
$p^*_{i,t+5}$	.001	.011	-.014	-.008	.007
		(.015)	(.015)	(.015)	(.015)
Pseudo R^2		.833	.842	.834	.847
#		406	406	406	406

Notes: * indicates t-test on difference from zero, * p<0.05, ** p<0.01, *italics* (**bold**) indicates t-test on difference of estimated coefficient from theoretical value at p<0.05 and p<0.01 respectively, robust standard errors in parentheses

Table 12: Estimated weights implied by set prices (with lagged desired prices in upper panel) across information categories in treatment 4

Dependent variable: $z_{i,t}$	(1)	(2)	(3)	(4)	(5)
	Prediction	*Very Uninformed Subjects*	*Relatively Uninformed Subjects*	*Relatively Informed Subjects*	*Very Informed Subjects*
$p^*_{i,t-5}$	0	.024	-.002	-.010	.009
		(.017)	(.011)	(.010)	(.016)
$p^*_{i,t-4}$	0	.014	.015	.003	.001
		(.016)	(.013)	(.009)	(.012)
$p^*_{i,t-3}$	0	.003	.015	-.016	-.014
		(.020)	(.014)	(.011)	(.013)
$p^*_{i,t-2}$	0	**-.082****	.026	-.001	-.023
		(.020)	(.019)	(.013)	(.014)
$p^*_{i,t-1}$	0	*.046**	.056	-.026	-.018
		(.023)	(.032)	(.014)	(.017)
$z_{i,t-1}$	.566	**.700****	.435**	**.753****	**.749****
		(.046)	(.098)	(.040)	(.064)
$p^*_{i,t}$	.189	**.252**	.229**	.164**	**.140****
		(.019)	(.021)	(.012)	(.016)
$p^*_{i,t+1}$	.107	**.010**	*.143***	**.071****	.097**
		(.018)	(.016)	(.010)	(.014)
$p^*_{i,t+2}$	.060	**.012**	.053**	**.032****	*.036***
		(.016)	(.012)	(.009)	(.011)
$p^*_{i,t+3}$	.034	.006	.023	.020*	*.008*
		(.017)	(.012)	(.009)	(.012)
$p^*_{i,t+4}$	.019	.013	**-.020**	.001	.011
		(.018)	(.011)	(.009)	(.010)
$p^*_{i,t+5}$	.011	.004	.021	.019	.002
		(.017)	(.013)	(.010)	(.011)
Pseudo R^2		.722	.869	.903	.837
#		232	232	232	232

Notes: * indicates t-test on difference from zero, * p<0.05, ** p<0.01, *italics* (**bold**) indicates t-test on difference of estimated coefficient from theoretical value at p<0.05 and p<0.01 respectively, robust standard errors in parentheses

4.2.2 WEIGHTS ON PAST SET PRICES

An alternative is that subjects seek information in their own past behavior – which is also heuristical behavior which has no theoretical foundation once the set price of the previous period is included.

To test whether past set prices influence price-setting, we estimate the following equation with OLS and robust standard errors:

$$z_{i,t} = \sum_{k=1}^{4} \alpha_k \, z_{i,t-k-1} + \beta z_{i,t-1} + \sum_{l=0}^{5} \gamma_l \, p^*_{i,t-l} + \varepsilon_{i,t} \qquad (14)$$

The first term on the RHS contains now four past set prices for which we do not have theoretical predictions. Because of the non-stationarity of the time series of desired prices we expect subjects to put more weight on past set prices in treatments 1 and 2.[14]

Table 13 displays the regression outputs for all observations of the four treatments. In treatments 1 and 2, the weight on the set price in the previous period becomes very large (compare the coefficients to the ones in Table 9). Treatments 1 and 2 also have significant a-theoretical backward-looking terms, as expected. In treatment 3 we observe two significant backward-looking terms and the coefficients with a theoretical prediction (other than zero) in the lower panel are indistinguishable from theory. In treatment 4, we observe (as in the previous section) too much weight on the set price in the previous period.

In Table 14 the outputs for the four information quartiles in treatment 2 are shown. Besides two large significant backward-looking terms in the upper panel the weights on

[14] To see whether the optimal time series contain significant backward-looking terms, we run $z^*_t = \sum_{k=1}^{4} \alpha_k \, z^*_{t-k-1} + \beta z^*_{t-1} + \sum_{l=0}^{5} \gamma_l \, p^*_{t-l} + \varepsilon_t$ for the four treatments. Regression outputs are shown in Table A5. Treatments 1 and 2 have both a significant coefficient of z^*_{t-3} and a much higher than predicted coefficient z^*_{t-1} because of the non-stationarity of the time series of desired prices. Treatment 3 and 4 have coefficients that are in line with predictions.

the own set price increase (almost monotonically) with the information acquired in the groups.

In Table 15 the outputs for the four information quartiles in treatment 3 are displayed. As in Table 11 in the previous section only very informed subjects in treatment 3 behave backward-looking. The forward-looking terms of the other categories are in line with theory (besides two weights).

Finally, Table 16 shows outputs for the four information quartiles in treatment 4. Again the less informed seek more information from past behavior. All but three weights on the set price in the previous period are larger than predicted.

Table 13: Estimated weights implied by set prices (with a-theoretical lagged set prices in upper panel) of all treatments

Dependent variable: $z_{i,t}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Treatment 1	Treatment 2	Treatment 3		Treatment 4	
	Prediction	Weight	Weight	Prediction	Weight	Prediction	Weight
$z_{i,t-5}$	0	-.003	-.025	0	*.026**	0	.024
		(.014)	(.020)		(.013)		(.036)
$z_{i,t-4}$	0	.017	.030	0	**-.044****	0	.033
		(.031)	(.035)		(.015)		(.050)
$z_{i,t-3}$	0	*-.079**	-.063	0	.017	0	-.044
		(.036)	(.034)		(.017)		(.046)
$z_{i,t-2}$	0	*-.011**	**-.227****	0	.031	0	-.047
		(.046)	(.060)		(.017)		(.045)
$z_{i,t-1}$	.800	**1.046****	**1.214****	.268	.235**	.566	**.714****
		(.042)	(.042)		(.018)		(.035)
$p^*_{i,t}$	.040	**-.022**	**-.060****	.536	.546**	.189	.184**
		(.022)	(.013)		(.012)		(.008)
$p^*_{i,t+1}$	.032	.047**	**.072***	.144	.130**	.107	**.074****
		(.014)	(.015)		(.008)		(.008)
$p^*_{i,t+2}$	.026	.050**	*.022**	.038	.032**	.060	**.033****
		(.013)	(.011)		(.008)		(.006)
$p^*_{i,t+3}$	.020	.016	-.003	.010	.008	.034	**.015***
		(.014)	(.011)		(.008)		(.006)
$p^*_{i,t+4}$	.016	.009	.022*	.003	.016*	.019	*.004*
		(.015)	(.010)		(.007)		(.006)
$p^*_{i,t+5}$	.013	.034**	.019*	.001	.003	.011	.011
		(.011)	(.007)		(.007)		(.006)
Pseudo R^2		.974	.979		.812		.804
#		2,109	1,881		1,767		1,026

Notes: * indicates t-test on difference from zero, * $p<0.05$, ** $p<0.01$, *italics* (**bold**) indicates t-test on difference of estimated coefficient from theoretical value at $p<0.05$ and $p<0.01$ respectively, robust standard errors in parentheses

Table 14: Estimated weights implied by set prices (with a-theoretical lagged set prices in upper panel) across information categories in treatment 2

Dependent variable: $z_{i,t}$	(1)	(2)	(3)	(4)	(5)
	Prediction	*Very Uninformed Subjects*	*Relatively Uninformed Subjects*	*Relatively Informed Subjects*	*Very Informed Subjects*
$z_{i,t-5}$	0	-.041	-.012	.038	-.012
		(.028)	(.043)	(.055)	(.027)
$z_{i,t-4}$	0	.049	.030	-.014	-.008
		(.056)	(.058)	(.099)	(.039)
$z_{i,t-3}$	0	.014	-.193	.068	-.105
		(.050)	(.100)	(.115)	(.061)
$z_{i,t-2}$	0	**-.213****	.003	**-.645****	-.134
		(.079)	(.123)	(.106)	(.128)
$z_{i,t-1}$	.800	**1.076****	**1.195****	**1.437****	**1.194****
		(.056)	(.072)	(.021)	(.097)
$p^*_{i,t}$	.040	-.035	**-.010**	**.113****	**-.039***
		(.041)	(.011)	(.026)	(.015)
$p^*_{i,t+1}$	.032	*.119***	.012	**.034**	.035*
		(.044)	(.016)	(.018)	(.017)
$p^*_{i,t+2}$	.026	.047	-.013	.005	.010
		(.030)	(.019)	(.019)	(.017)
$p^*_{i,t+3}$	.020	*-.041*	.038	.028	-.001
		(.027)	(.021)	(.020)	(.017)
$p^*_{i,t+4}$	.016	.020	-.011	.036*	.049*
		(.021)	(.019)	(.014)	(.020)
$p^*_{i,t+5}$	.013	.000	.021	.045**	.010
		(.016)	(.014)	(.015)	(.015)
Pseudo R^2		.964	.984	.992	.982
#		456	456	456	456

Notes: * indicates t-test on difference from zero, * p<0.05, ** p<0.01, *italics* (**bold**) indicates t-test on difference of estimated coefficient from theoretical value at p<0.05 and p<0.01 respectively, robust standard errors in parentheses

Table 15: Estimated weights implied by set prices (with a-theoretical lagged set prices in upper panel) across information categories in treatment 3

Dependent variable: $z_{i,t}$	(1) Prediction	(2) *Very Uninformed Subjects*	(3) *Relatively Uninformed Subjects*	(4) *Relatively Informed Subjects*	(5) *Very Informed Subjects*
$z_{i,t-5}$	0	.029	.021	.023	-.001
		(.021)	(.027)	(.027)	(.028)
$z_{i,t-4}$	0	-.033	-.028	-.053	-.005
		(.026)	(.028)	(.030)	(.034)
$z_{i,t-3}$	0	.013	.013	.035	-.005
		(.032)	(.032)	(.031)	(.030)
$z_{i,t-2}$	0	**.071****	.015	.016	-.030
		(.027)	(.038)	(.031)	(.031)
$z_{i,t-1}$	.268	**.151****	.230**	.208**	*.355***
		(.026)	(.038)	(.026)	(.035)
$p^*_{i,t}$	.536	**.658****	.561**	.570**	.496**
		(.024)	(.024)	(.017)	(.021)
$p^*_{i,t+1}$	.144	**.089****	.146**	.033*	.125**
		(.019)	(.016)	(.016)	(.015)
$p^*_{i,t+2}$	.038	**-.008**	.024	.014	.052**
		(.016)	(.014)	(.017)	(.013)
$p^*_{i,t+3}$	.010	.019	-.009	.014	-.001
		(.016)	(.017)	(.018)	(.015)
$p^*_{i,t+4}$	.003	.003	*.033**	.004	.004
		(.016)	(.015)	(.014)	(.014)
$p^*_{i,t+5}$	.001	.009	-.010	-.003	.014
		(.015)	(.015)	(.015)	(.014)
Pseudo R^2		.821	.845	.839	.855
#		399	399	399	399

Notes: * indicates t-test on difference from zero, * p<0.05, ** p<0.01, *italics* (**bold**) indicates t-test on difference of estimated coefficient from theoretical value at p<0.05 and p<0.01 respectively, robust standard errors in parentheses

Table 16: Estimated weights implied by set prices (with a-theoretical lagged set prices in upper panel) across information categories in treatment 4

Dependent variable: $z_{i,t}$	(1)	(2)	(3)	(4)	(5)
	Prediction	*Very Uninformed Subjects*	*Relatively Uninformed Subjects*	*Relatively Informed Subjects*	*Very Informed Subjects*
$z_{i,t-5}$	0	**.152****	-.101	-.002	*.092**
		(.054)	(.071)	(.039)	(.043)
$z_{i,t-4}$	0	-.153	*.181**	.016	-.007
		(.082)	(.082)	(.062)	(.082)
$z_{i,t-3}$	0	*.193**	**-.16****	-.051	-.077
		(.083)	(.039)	(.066)	(.084)
$z_{i,t-2}$	0	**-.298****	.118	-.030	-.007
		(.077)	(.061)	(.072)	(.082)
$z_{i,t-1}$	.566	**.810****	.551**	**.751****	.707**
		(.055)	(.052)	(.040)	(.077)
$p^*_{i,t}$	.189	**.250****	.209**	.165**	**.141****
		(.019)	(.013)	(.010)	(.016)
$p^*_{i,t+1}$	.107	**.005**	.129**	**.072****	.095**
		(.017)	(.014)	(.010)	(.014)
$p^*_{i,t+2}$	.060	**.015**	.060**	**.034****	*.035***
		(.015)	(.010)	(.009)	(.011)
$p^*_{i,t+3}$	.034	*.001*	.015	.025*	.009
		(.017)	(.010)	(.010)	(.012)
$p^*_{i,t+4}$	.019	.021	*-.010*	.020	.013
		(.018)	(.010)	(.009)	(.010)
$p^*_{i,t+5}$	.011	.005	.008	.020	-.002
		(.017)	(.009)	(.010)	(.011)
Pseudo R^2		.726	.898	.903	.843
#		228	228	228	228

Notes: * indicates t-test on difference from zero, * p<0.05, ** p<0.01, *italics* (**bold**) indicates t-test on difference of estimated coefficient from theoretical value at p<0.05 and p<0.01 respectively, robust standard errors in parentheses

4.3 IMPLICATIONS FOR THE NEW KEYNESIAN PHILLIPS CURVE

In this section we tackle the question what the previous findings mean for the New Keynesian Phillips curve. In the previous section we found little evidence for weights that subjects put on past information, so we estimate both a purely forward-looking and a hybrid NKPC and discuss our findings.

In the appendix we derive a forward-looking NKPC of the following form:

$$\Delta z_t = \frac{1}{1+c}(p_t^* - z_{t-1}) + \frac{c}{1+c}\Delta E_t z_{t+1} \tag{13}$$

This is not a NKPC of the form in Equation (4) because the equation does not contain an output gap (from which we abstracted in our experiment) and the weight on future inflation is not equal to unity. But as it does not come with some assumptions that some authors need to specify in order to derive Equation (4), we decide to work with this one.[15] The first term on the RHS is the deviation of the current desired price from the past set price and the second term is equivalent to the expected future inflation. We consider Equation (13) as a stylized NKPC with the advantage that only the cost parameter c is needed to calculate the predicted weights on the first, the deviation term and expected future inflation.

We extend Equation (13) by a constant and estimate its coefficients with our pooled data:

$$\Delta z_{i,t} = \alpha + \beta_1\left(p_{i,t}^* - z_{i,t-1}\right) + \beta_2 \Delta z_{i,t+1} + \varepsilon_{i,t} \tag{14}$$

Table 17 shows the outputs of the linear regressions with the constraint $\beta_1 + \beta_2 = 1$ and robust standard errors of Equation (14). The table gives also the theoretical predictions

[15] E.g. Roberts (1995) derives a NKPC like the one in Equation (4). He uses the assumption that on average all (identical) firms set a price that is equal to the desired price of the period, $p_t = p_t^*$, to derive his NKPC. We do not want to use this assumption as the desired prices in our experiment are clearly exogenous and setting prices equal to them would result in very low profits.

as a benchmark.[16] First we look at all observations across our treatments. In all four treatments the weight on the future inflation term is smaller than predicted, as found in empirical studies (e.g. Schorfheide, 2008).

We then look at the differently informed groups within Information for Effort treatments, treatments 2, 3 and 4. In all these treatments the subjects in the more informed categories put weights on the forward-looking term that is indistinguishable from theoretical predictions. In contrast to that, the less informed subjects set prices that imply a weight on the forward-looking term that is smaller than predicted (except the relatively uninformed in treatments 2 and 4 whose weight on β_2 is bigger than predicted). We conclude from the results of this estimation that the driver of the weight on the forward-looking term at the aggregate (treatment) level is the behavior of the uninformed subjects.

The specification estimated with Equation (14) does not account for a backward-looking term like the hybrid NKPC in Equation (5). As we found some evidence of backward-looking behavior (beyond prices for which theory predicts positive weights) for the less informed subjects and more weight on the past set price than theoretically predicted for many categories and treatments, we also estimate a hybrid version of the NKPC with an a-theoretical backward-looking term:

$$\Delta z_{i,t} = \alpha + \beta_1 \Delta z_{i,t-1} + \beta_2 \left(p^*_{i,t} - z_{i,t-1}\right) + \beta_3 \Delta z_{i,t+1} + \varepsilon_{i,t} \qquad (15)$$

Table 18 displays the estimates of linear regressions with the constraint $\beta_1 + \beta_2 + \beta_3 = 1$ and robust standard errors of Equation (15).

[16] We implicitly assume here that subjects in period t already form expectations about the price they set in the next period $t + 1$.

We observe significant backward-looking behavior in all treatments, both at the aggregate level and when we look at the information categories separately.[17]

At the treatment level, the weight on the backward-looking inflation term increases with the cost parameter in the treatments.

In treatment 2, the weights on future and past inflation have about the same size (about 45-50%) and do not differ much across the information categories. In treatment 3, the weight on past inflation is much lower, between 5% and 14%. In treatment 4 it ranges between 19% and 42%. In both treatments the weights on the past inflation terms do not vary with the information category. The weights that the very uninformed in treatments 3 and 4 put on future inflation is much lower than the weight of the more informed subjects.

Which of the two Phillips curves is the "right" one? As stated before, the range that Schorfheide (2008) finds for the weights on future and past inflation is wide, so we conclude that we cannot exclude either one of the (stylized) Phillips curves on grounds of "unrealistic" values of the weights. When we compare the two NKPCs by information criteria, we find that both the Akaike information criterion (AIC) and the Bayesian information criterion (BIC) prefer the hybrid NKPC.[18]

[17] To exclude the possibility that a-theoretical backward-looking terms play a role in regressions that use optimal prices instead of set prices, we estimate $\Delta z_{i,t}^{*} = \alpha + \beta_1 \Delta z_{i,t-1}^{*} + \beta_2 \left(p_{i,t}^{*} - z_{i,t-1}^{*}\right) + \beta_3 \Delta z_{i,t+1}^{*} + \varepsilon_{i,t}$ with the constraint $\beta_1 + \beta_2 + \beta_3 = 1$ and robust standard errors. The output is given in Table A 5 in the appendix. The weights on both backward and forward-looking inflation term are in line with theory, though in treatments 1 and 2 coefficient β_1 is large.

18 To adjust for serial correlation we also perform Cochrane-Orcutt regressions. Table A7 shows the estimation outputs for Cochrane-Orcutt regressions with robust standard errors of the forward-looking NKPC in Equation (14). Table A8 the outputs for the hybrid NKPC in Equation (15). In both regressions the error term $\varepsilon_{i,t}$ is substituted by $\varepsilon_t = \rho\varepsilon_{t-1} + e_t$. To make the estimates comparable with Table 17 and 18, we imposed the constraints $\beta_1 + \beta_2 = 1$ (Table 19) and $\beta_1 + \beta_2 + \beta_3 = 1$ (Table 20). The Cochrane-Orcutt regressions are conducted using Stata command `prais` in the first stage and the constraints in a second stage with `linest`. AIC, BIC, R^2 and ρ in the tables belong to the first stage.

Nonetheless can we find support at the micro level for the purely forward-looking NKPC and the weights we estimated using it across the information categories. When we consider the findings of section 4.1, we find different behavior by information category in all treatments and that more informed subjects set prices that are closer to optimal prices and that less informed subjects do not smooth enough. The consequences of this behavior are found in the weights that we estimate with the purely forward-looking Phillips curve.

These findings from section 4.1 are not found that clearly in the weights of the hybrid Phillips curves. We observe that in treatments 3 and 4 the weights that the subjects in the least informed category put on future inflation are much smaller than that of the more informed categories (the most informed categories weights on future inflation are not indistinguishable from theory, though).

The main result of the hybrid NKPC, the significant backward-looking terms across treatments and information categories, are reflected in another of our previous findings. In section 4.2 we found (in both approaches in sections 4.2.1 and 4.2.2) that subjects put too much weight on the past desired price z_{t-1} which can be interpreted as price stickiness. The variation of the weights in Tables 10, 11 and 12 (but also in Tables 14, 15 and 16) across information categories can be found in the varying weights in the hybrid NKPC in Table 18.

The ρs in Table A7 and A8 are high. When we compare Table A7 with Table 17, the main result survives: the category of very uninformed subjects puts a smaller weight on future inflation than the more informed subjects. Also Table A8 shows essentially the same results for the hybrid NKPC as Table 18.

Table 17: Estimated coefficients in the purely forward-looking NKPC across treatments and information categories

	α	β_1	β_2	n	AIC	BIC	R^2
Treatment 1							
Theoretical weights	0	.0476	.9524				
All observations	-.025	**.144****	**.856****	2,220	5,818.0	5,829.4	.211*
	(.02)	(.02)	(.02)				
Treatment 2							
Theoretical weights	0	.0476	.9524				
All observations	*-.043**	*.072***	*.928***	1,980	4,544.7	4,555.9	.133
	(.27)	(.01)	(.01)				
Very uninformed	-.064	**.141****	**.859****	480	1,398.4	1,406.8	.242
	(.05)	(.03)	(.03)				
Relatively uninformed	-.001	**.019***	**.981****	480	976.6	984.9	.141
	(.03)	(.01)	(.01)				
Relatively informed	-.025	.076**	.924**	480	743.0	751.3	.339
	(.03)	(.02)	(.02)				
Very informed	-.057	.061**	.939**	480	971.7	980.0	.121
	(.04)	(.02)	(.02)				
Treatment 3							
Theoretical weights	0	.6667	.3333				
All observations	-.038	**.753****	**.247****	1,860	12,217.2	12,228.2	.678
	(.15)	(.01)	(.01)				
Very uninformed	.222	**.861****	**.139****	420	2,780.8	2,788.9	.771
	(.32)	(.01)	(.01)				
Relatively uninformed	-.318	**.748****	**.252****	420	2,684.8	2,692.9	.723
	(.29)	(.02)	(.02)				
Relatively informed	-.064	**.760****	**.240****	420	2,709.5	2,717.6	.722
	(.30)	(.02)	(.02)				
Very informed	.211	.676**	.324**	420	2,646.9	2,655.0	.696
	(.21)	(.02)	(.02)				
Treatment 4							
Theoretical weights	0	.25	.75				
All observations	-.026	*.281***	*.719***	1,080	6,382.5	6,392.5	.040
	(.14)	(.01)	(.01)				
Very uninformed	-.161	**.336****	**.664****	240	1,552.6	1,559.6	.055
	(.40)	(.03)	(.03)				
Relatively uninformed	.077	**.081***	**.919****	240	1,417.8	1,424.7	.177
	(.33)	(.04)	(.04)				
Relatively informed	.130	.240**	.760**	240	1,205.4	1,212.3	.383
	(.19)	(.02)	(.02)				
Very informed	-.111	.223**	.777**	240	1,336.9	1,343.9	.070
	(.25)	(.02)	(.02)				

Notes: * indicates t-test on difference from zero, * p<0.05, ** p<0.01, *italics* (**bold**) indicates t-test on difference of estimated coefficient from theoretical value at p<0.05 and p<0.01 respectively, robust standard errors in parentheses

Table 18: Estimated coefficients in the hybrid NKPC across treatments and information categories

	α	β_1	β_2	β_3	n	AIC	BIC	R^2
<u>Treatment 1</u>								
Theoretical weights	0	0	.0476	.9524				
All observations	-.023	**.456****	**.105****	.439**	2,183	5,097.5	5,114.5	.060
	(.02)	(.05)	(.01)	(.05)				
<u>Treatment 2</u>								
Theoretical weights	0	0	.0476	.9524				
All observations	-.035*	**.479****	.049**	**.472****	1,947	3,788.7	3,805.4	.191
	(.02)	(.05)	(.01)	(.05)				
Very uninformed	-.046	**.456****	*.098***	**.446****	472	1,226.3	1,238.7	.057
	(.04)	(.07)	(.02)	(.07)				
Relatively uninformed	-.023	**.496****	**.023***	**.481****	472	810.9	823.3	.125
	(.03)	(.12)	(.01)	(.12)				
Relatively informed	-.006	**.487****	**.016**	**.496****	472	467.2	479.7	.628
	(.02)	(.06)	(.02)	(.06)				
Very informed	-.046	**.482****	.044**	**.475****	472	810.6	823.1	.173
	(.03)	(.02)	(.02)	(.14)				
<u>Treatment 3</u>								
Theoretical weights	0	0	.6667	.3333				
All observations	-.043	**.082****	**.726****	**.191****	1,829	11,971.6	11,988.1	.686
	(.15)	(.01)	(.01)	(.01)				
Very uninformed	.213	**.053****	**.844****	**.103****	413	2,733.4	2,745.5	.776
	(.32)	(.02)	(.02)	(.02)				
Relatively uninformed	-.323	**.067****	**.724****	**.208****	413	2,635.7	2,647.9	.730
	(.29)	(.02)	(.02)	(.02)				
Relatively informed	-.064	**.051***	**.742****	**.207****	413	2,665.7	2,677.8	.727
	(.30)	(.03)	(.03)	(.02)				
Very informed	.230	**.142****	**.631****	**.226****	413	2,554.3	2,566.4	.719
	(.26)	(.02)	(.02)	(.02)				
<u>Treatment 4</u>								
Theoretical weights	0	0	.25	.75				
All observations	-.053	**.333****	.235**	**.432****	1,062	6,028.9	6,043.8	.249
	(.13)	(.03)	(.01)	(.03)				
Very uninformed	-.198	**.428****	*.304***	**.268****	236	1,406.7	1,417.1	.375
	(.31)	(.04)	(.02)	(.04)				
Relatively uninformed	-.112	**.192****	.294**	**.514****	236	1,381.3	1,391.7	.237
	(.29)	(.07)	(.03)	(.07)				
Relatively informed	.052	**.259****	**.203****	**.538****	236	1,140.1	1,150.5	.499
	(.17)	(.04)	(.02)	(.04)				
Very informed	-.115	**.315****	**.171****	**.514****	236	1,273.8	1,284.2	.235
	(.23)	(.07)	(.02)	(.07)				

Notes: * indicates t-test on difference from zero, * p<0.05, ** p<0.01, *italics* (**bold**) indicates t-test on difference of estimated coefficient from theoretical value at p<0.05 and p<0.01 respectively, robust standard errors in parentheses

5 Conclusion

We test the Rotemberg (1982) model by designing lab experiments in which subjects in various treatments are either shown all future desired prices or have to decide if and how many of them to acquire and finally set prices[19].

In a first step we analyze subjects' behavior by ignoring the intertemporal dimension of the optimization problem. To achieve that we construct conditional optimal prices which subjects should use given their own past behavior (that might not have been optimal). We find that more informed subjects set prices that are closer to conditional optimal prices and that less informed subjects in all treatments do not smooth enough as the cost parameters in the different treatments imply.

In a second step we estimate weighting schemes that the subjects' set prices in our experiment imply. The empirically observed weighting scheme on theoretically predicted past set and current and past desired prices has the form of the prediction, though in general too much weight is put on the past own set price. Subjects rarely seek information in desired or own set prices that they theoretically should not consider at all in their decision-making.

Finally we estimate both purely forward-looking and hybrid New Keynesian Phillips curves. The hybrid Phillips curve with positive weights on a-theoretical backward-looking inflation is preferred by information criteria. The backward-looking behavior in the Phillips curves is also found at the micro level where firms stick too much to their own past price of the previous period.

[19] The differences between treatment 1 and 2 are small. Subjects in treatment 1earned about the same amount of points as in treatment 2 (see Table A1), used similar weights (see Table 9) and the resulting NKPCs are also similar to treatment 2 (see Table 13 and 14).

The estimated coefficients in the purely forward-looking NKPC reflect the findings that ignore the intertemporal dimension of the price-setting problem of the firms. Very uninformed subjects put much less weight on future inflation in the theoretical derived NKPC than the other groups.

Our results show that subjects in all information categories have problems to set optimal prices and stick too much to the price they set in the previous period. This behavior might be explained by anchoring or the status quo bias (Tversky and Kahneman, 1974; Samuelson and Zeckhauser, 1988). More informed subjects in our experiments set prices that imply Phillips curves that are closer to predictions. This finding is in line with the previous chapter where myopic agents also influenced the form the Phillips curve.

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APPENDIX

Figure A1: Screenshot of the Free Information treatment (1)

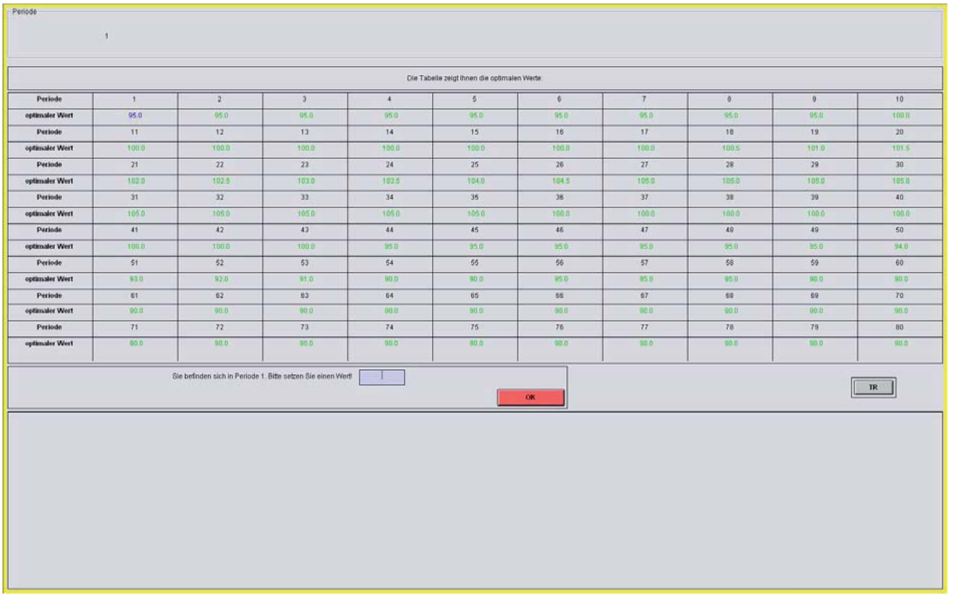

Figure A2: Screenshot of the Information for Effort treatments (2, 3 and 4)

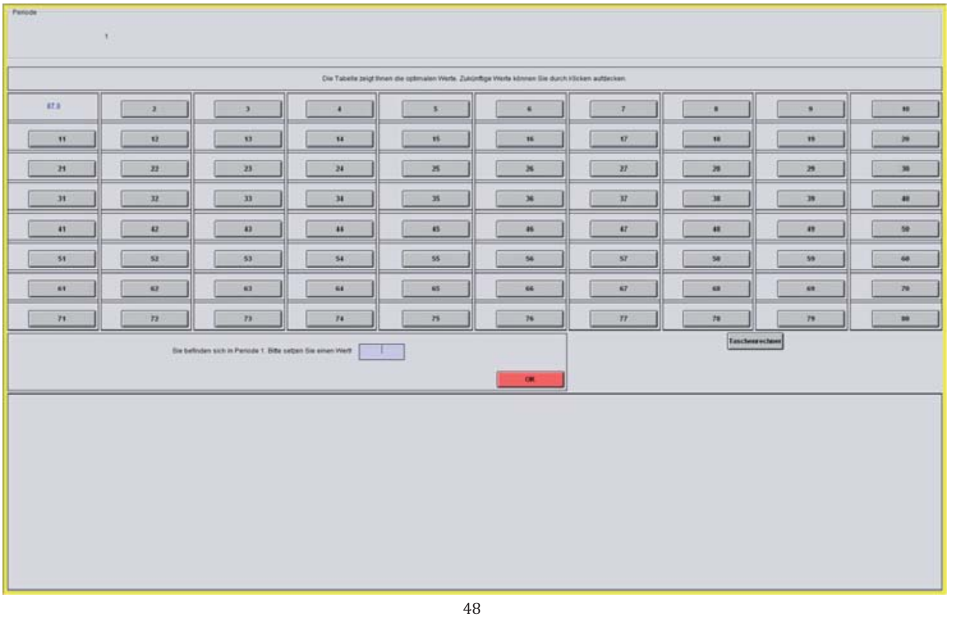

Table A1: Total profits by treatment and information category

	All subjects without dropouts	*Very Uninformed Subjects*	*Relatively Uninformed Subjects*	*Relatively Informed Subjects*	*Very Informed Subjects*	*Jonckhere-Terpstra test (ascending ordered alternative)*
Treatment 1	1,605.2					
	(900.1)					
Treatment 2	1,653.8	1,279.09	1,627.2	1,945.3	1,754.3	$J^* = 1.966$
	(524.0)	(587.6)	(582.3)	(248.4)	(488.3)	p=.0246
Treatment 3	16,320.4	15,614.3	17,064.1	16,766.7	16,184.0	$J^* = .532$
	(2,719.3)	(2,835.7)	(1,918.5)	(2,143.5)	(4,052.1)	p=.2972
Treatment 4	11,329.9	8,508.6	12,052.4	13,105.3	12,279.9	$J^* = 1.774$
	(2,808.3)	(2,269.8)	(453.9)	(1,764.8)	(782.6)	p=.0380

Notes: Standard deviations in parentheses.

Table A2: Behavioral categories by information categories during booms (treatments 2, 3, 4)

		Information Acquisition				Total
		Very Uninformed Subjects	*Relatively Uninformed Subjects*	*Relatively Informed Subjects*	*Very Informed Subjects*	
Category of Behavior during Booms	Too much Smoothing	185 (27.13%)	219 (33.13%)	187 (26.76%)	250 (36.82%)	841 (30.91%)
	Optimal behavior	103 (15.10%)	135 (20.42%)	184 (26.32%)	160 (23.56%)	582 (21.39%)
	Some smoothing	153 (22.43%)	134 (20.27%)	123 (17.60%)	115 (16.94%)	525 (19.29%)
	No smoothing	195 (28.59%)	146 (22.09%)	158 (22.60%)	118 (17.38%)	617 (22.68%)
	Too extreme	46 (6.74%)	27 (4.08%)	47 (6.72%)	36 (5.30%)	156 (5.73%)
Total		682 (100%)	661 (100%)	699 (100%)	679 (100%)	2,721 (100%)

Note: Cell frequencies and row percentages in brackets

Table A3: Behavioral categories by information acquisition during busts (treatments 2, 3, 4)

		Information Acquisition				Total
		Very Uninformed Subjects	*Relatively Uninformed Subjects*	*Relatively Informed Subjects*	*Very Informed Subjects*	
Category of Behavior during Busts	Too much Smoothing	184 (37.10%)	203 (39.26%)	203 (42.38%)	247 (49.50%)	837 (42.04%)
	Optimal behavior	54 (10.89%)	71 (13.73%)	63 (13.15%)	61 (12.22%)	249 (12.51%)
	Some smoothing	116 (23.39%)	130 (25.15%)	115 (24.01%)	95 (19.04%)	456 (22.90%)
	No smoothing	116 (23.39%)	103 (19.92%)	85 (17.75%)	89 (17.84%)	393 (19.74%)
	Too extreme	26 (5.24%)	10 (1.93%)	13 (2.71%)	7 (1.40%)	56 (2.81%)
Total		496 (100%)	517 (100%)	479 (100%)	499 (100%)	1,991 (100%)

Note: Cell frequencies and column percentages in brackets

Table A4: Estimated weights implied by optimal prices (with lagged desired prices in upper panel) in all treatments

Dependent variable: z_t^*	(1)	(2)	(3)	(4)	(5)	(6)
		Treatment 1 and 2		Treatment 3		Treatment 4
	Prediction	Weight	Prediction	Weight	Prediction	Weight
p_{t-5}^*	0	**-.036****	0	**.001****	0	*-.005**
		(.012)		(.000)		(.002)
p_{t-4}^*	0	.016	0	.003	0	**-.009****
		(.010)		(.001)		(.002)
p_{t-3}^*	0	*-.023**	0	.010	0	**-.016****
		(.011)		(.005)		(.003)
p_{t-2}^*	0	-.010	0	.036	0	**-.027****
		(.013)		(.018)		(.006)
z_{t-1}^*	.800	*.868***	.268	.036	.566	**.747****
		(.034)		(.118)		(.039)
p_t^*	.040	.043**	.536	.572**	.189	**.161****
		(.011)		(.018)		(.006)
p_{t+1}^*	.032	.018	.144	.153**	.107	**.090****
		(.011)		(.005)		(.004)
p_{t+2}^*	.026	.039**	.038	.041**	.060	**.051****
		(.014)		(.001)		(.003)
p_{t+3}^*	.020	.023	.010	.011**	.034	**.029****
		(.012)		(.000)		(.002)
$p_{i,t+4}^*$	.016	.011	.003	.003**	.019	.017**
		(.008)		(.000)		(.002)
p_{t+5}^*	.013	**.049****	.001	.001**	.011	.011**
		(.008)		(.000)		(.001)
Pseudo R^2		.907		.924		.846
#		58		58		58

Notes: * indicates t-test on difference from zero, * p<0.05, ** p<0.01, *italics* (**bold**) indicates t-test on difference of estimated coefficient from theoretical value at p<0.05 and p<0.01 respectively, robust standard errors in parentheses

Table A5: Estimated weights implied by optimal prices (with lagged optimal set prices in upper panel) in all treatments

Dependent variable: z_t^*	(1)	(2)	(3)	(4)	(5)	(6)
		Treatment 1 and 2	Treatment 3		Treatment 4	
	Prediction	Weight	Prediction	Weight	Prediction	Weight
z_{t-5}^*	0	.001	0	*.001**	0	.009
		(.097)		(.000)		(.007)
z_{t-4}^*	0	.210	0	-.001	0	-.004
		(.198)		(.001)		(.012)
z_{t-3}^*	0	**-.487****	0	-.000	0	-.004
		(.224)		(.001)		(.012)
z_{t-2}^*	0	-.164	0	.001	0	.007
		(.223)		(.001)		(.012)
z_{t-1}^*	.800	**1.334****	.268	.268**	.566	.570**
		(.149)		(.000)		(.001)
p_t^*	.040	.018	.536	.536**	.189	.188**
		(.012)		(.000)		(.002)
p_{t+1}^*	.032	*.010*	.144	.143**	.107	.106**
		(.008)		(.000)		(.001)
p_{t+2}^*	.026	.029**	.038	.038**	.060	.051**
		(.009)		(.000)		(.001)
p_{t+3}^*	.020	.010	.010	*.010***	.034	.060**
		(.011)		(.000)		(.001)
$p_{i,t+4}^*$	.016	.014	.003	.003**	.019	.020**
		(.012)		(.000)		(.001)
p_{t+5}^*	.013	.025*	.001	.001*	.011	.013**
		(.011)		(.000)		(.001)
Pseudo R^2		1		1		1
#		57		57		57

Notes: * indicates t-test on difference from zero, * p<0.05, ** p<0.01, *italics* (**bold**) indicates t-test on difference of estimated coefficient from theoretical value at p<0.05 and p<0.01 respectively, robust standard errors in parentheses

Table A6: Estimated coefficients for optimal prices in the hybrid NKPC across treatments

	α	β_1	β_2	β_3	n	Pseudo R^2
Treatments 1 and 2						
Theoretical weight in forward-looking NKPC	0	0	.0476	.9524		
Estimation	-.030	.235	.036*	.729**	59	.962
	(.02)	(.17)	(.02)	(.16)		
Treatment 3						
Theoretical weight in forward-looking NKPC	0	0	.6667	.3333		
Estimation	.002	-.000	.667**	.334**	59	1
	(.00)	(.00)	(.00)	(.00)		
Treatment 4						
Theoretical weight in forward-looking NKPC	0	0	.25	.750		
Estimation	-.000	-.000	.250**	.750**	59	1
	(.01)	(.00)	(.00)	(.00)		

Notes: * indicates t-test on difference from zero, * p<0.05, ** p<0.01, *italics* (**bold**) indicates t-test on difference of estimated coefficient from theoretical prediction of the purely forward-looking NKPC at p<0.05 and p<0.01 respectively, robust standard errors in parentheses

Table A7: Coefficients in the purely forward-looking NKPC across treatments and information categories estimated with Cochrane-Orcutt (AR(1))

	α	β_1	β_2	ρ	n	AIC	BIC	R^2
Treatment 1								
Theoretical weights	0	.0476	.9524					
All observations	-.047	**.212****	**.788****	.610	2,183	4,713.5	4,730.6	.235
	(.04)	(.02)	(.02)					
Treatment 2								
Theoretical weights	0	.0476	.9524					
All observations	*-.083**	.077**	.923**	.617	1,947	3,703.3	3,720.0	.147
	(.04)	(.02)	(.02)					
Very uninformed	-.105	**.278****	**.722****	.579	472	1,122.2	1,134.7	.277
	(.09)	(.04)	(.04)					
Relatively uninformed	-.011	**.010***	**.990****	-.319	472	772.3	784.7	.409
	(.02)	(.00)	(.00)					
Relatively informed	-.023	.076**	.924**	.454	472	665.1	677.6	.088
	(.04)	(.02)	(.02)					
Very informed	.005	**.019***	**.980****	-.654	472	805.7	818.1	.365
	(.02)	(.01)	(.01)					
Treatment 3								
Theoretical weights	0	.6667	.3333					
All observations	-.014	**.759****	**.241****	-.210	1,829	11,578.5	11,595.0	.732
	(.11)	(.01)	(.01)					
Very uninformed	*.439**	**.863****	**.137****	-.389	413	2,570.5	2,582.5	.825
	(.19)	(.01)	(.01)					
Relatively uninformed	-.140	**.750****	**.250****	-.235	413	2,562.7	2,574.8	.764
	(.21)	(.02)	(.02)					
Relatively informed	-.245	**.771****	**.229****	-.164	413	2,615.7	2,627.8	.746
	(.24)	(.02)	(.02)					
Very informed	.159	.687**	.313**	-.070	413	2,501.5	2,513.6	.750
	(.22)	(.02)	(.02)					
Treatment 4								
Theoretical weights	0	.25	.75					
All observations	.027	.243**	.757**	-.188	1,062	5,680.6	5,695.5	.493
	(.09)	(.01)	(.01)					
Very uninformed	.254	**.385****	**.615****	.092	236	1,329. 4	1,339.8	.552
	(.29)	(.02)	(.02)					
Relatively uninformed	-.117	.272**	.728**	-.561	236	1,238.1	1,248.5	.703
	(.13)	(.01)	(.01)					
Relatively informed	.120	**.213****	**.787****	-.127	236	1,084.4	1,094.8	.629
	(.14)	(.01)	(.01)					
Very informed	-.428	**.203****	**.797****	-.276	236	1,215.3	1,225.7	.494
	(.15)	(.02)	(.02)					

Notes: * indicates t-test on difference from zero, * p<0.05, ** p<0.01, *italics* (**bold**) indicates t-test on difference of estimated coefficient from theoretical value at p<0.05 and p<0.01 respectively, robust standard errors in parentheses

Table A8: Coefficients in the hybrid NKPC across treatments and information categories estimated with Cochrane-Orcutt (AR(1))

	α	β_1	β_2	β_3	ρ	n	AIC	BIC	R^2
Treatment 1									
Theoretical weights	0	0	.0476	.9524					
All observations	-.005	**.508****	**.022****	**.469****	-.647	2,146	4,039.2	4,061.9	.668
	(.01)	(.03)	(.00)	(.02)					
Treatment 2									
Theoretical weights	0	0	.0476	.9524					
All observations	-.007	**.518****	**.012****	**.470****	-.619	1,914	2,915.5	2,937.7	.718
	(.01)	(.03)	(.00)	(.03)					
Very uninformed	-.015	**.483****	*.030***	**.488****	-.578	464	1,044.4	1,061.0	.598
	(.02)	(.04)	(.01)	(.04)					
Relatively uninformed	-.007	**.483****	**.005***	**.511****	-.700	464	503.1	519.7	.774
	(.01)	(.07)	(.00)	(.07)					
Relatively informed	.004	**.495****	**.000**	**.505****	-.481	464	355.6	372.2	.842
	(.01)	(.04)	(.01)	(.04)					
Very informed	.004	**.527****	*.009**	**.463****	-.654	464	568.4	585.0	.744
	(.01)	(.06)	(.00)	(.06)					
Treatment 3									
Theoretical weights	0	0	.6667	.3333					
All observations	.089	**.086****	*.693***	**.220****	-.168	1,798	11,393.7	11,415.6	.735
	(.12)	(.01)	(.01)	(.01)					
Very uninformed	.437*	**.048****	**.818****	**.133****	-.320	406	2,520.7	2,536.7	.832
	(.20)	(.01)	(.02)	(.01)					
Relatively uninformed	-.029	**.089****	.687**	**.224****	-.231	406	2,525.7	2,541.7	.765
	(.22)	(.03)	(.02)	(.02)					
Relatively informed	-.091	**.058***	.713**	**.230****	-.129	406	2,575.3	2,591.4	.750
	(.25)	(.02)	(.03)	(.02)					
Very informed	.202	**.132****	**.598****	**.269****	-.154	406	2,462.3	2,478.3	.752
	(.21)	(.02)	(.02)	(.02)					
Treatment 4									
Theoretical weights	0	0	.25	.75					
All observations	-.050	**.375****	**.153****	**.472****	-.532	1,044	5,515.8	5,535.6	.637
	(.07)	(.02)	(.01)	(.02)					
Very uninformed	-.193	**.424****	**.313****	**.263****	-.027	232	1,310.2	1,323.9	.556
	(.26)	(.03)	(.02)	(.04)					
Relatively uninformed	-.091	**.287****	**.198****	**.515****	-.723	232	1,193.3	1,207.1	.776
	(.12)	(.04)	(.02)	(.03)					
Relatively informed	.083	**.345****	**.144****	**.510****	-.387	232	1,058.3	1,072.1	.713
	(.11)	(.05)	(.01)	(.03)					
Very informed	-.097	**.367****	**.118****	**.515****	-.600	232	1,162.6	1,176.4	.679
	(.11)	(.05)	(.02)	(.04)					

Notes: * indicates t-test on difference from zero, * p<0.05, ** p<0.01, *italics* (**bold**) indicates t-test on difference of estimated coefficient from theoretical value at p<0.05 and p<0.01 respectively, robust standard errors in parentheses

Derivation of the NKPC (following the approach in Wickens (2011, pp. 234-235)

The minimization problem of our firm (without the discount factor in Equation (1)) is:

$$\min_{\{z_t\}_{t=0}^{\infty}} E_t \sum_{k=0}^{\infty} [(z_{t+k} - p_{t+k}^*)^2 + c(z_{t+k} - z_{t+k-1})^2]$$

The FOC of it is:

$$2E_t\{(z_{t+k} - p_{t+k}^*) + c(z_{t+k} - z_{t+k-1}) - c(z_{t+k+1} - z_{t+k})\} = 0$$

We set $k = 0$:

$$2\{(z_t - p_t^*) + c(z_t - z_{t-1}) - c(E_t z_{t+1} - z_t)\} = 0$$

Now dividing by 2, and rearranging so $(z_t - p_t^*)$ and $c(E_t z_{t+1} - z_t)$ get on the RHS:

$$c(z_t - z_{t-1}) = -(z_t - p_t^*) + c(E_t z_{t+1} - z_t)$$

Minus $(-cz_{t-1})$ and plus z_t:

$$(1 + c)z_t = p_t^* + cz_{t-1} + c(E_t z_{t+1} - z_t)$$

Dividing by $(1 + c)$:

$$z_t = \frac{1}{1 + c} p_t^* + \frac{c}{1 + c} z_{t-1} + \frac{c}{1 + c}(E_t z_{t+1} - z_t)$$

Minus z_{t-1} on both sides:

$$z_t - z_{t-1} = \frac{1}{1 + c} p_t^* + (\frac{c}{1 + c} - \frac{1 + c}{1 + c}) z_{t-1} + \frac{c}{1 + c}(E_t z_{t+1} - z_t)$$

$$z_t - z_{t-1} = \frac{1}{1 + c}(p_t^* - z_{t-1}) + \frac{c}{1 + c}(E_t z_{t+1} - z_t)$$

$$\Delta z_t = \frac{1}{1 + c}(p_t^* - z_{t-1}) + \frac{c}{1 + c} E_t \Delta z_{t+1}$$

This is a New Keynesian Phillips curve where the price change today depends on the firm's deviation of the current desired price from the past set price and the expected price change in the next period.

Iteration:

$$\Delta z_t = \frac{1}{1+c}(p_t^* - z_{t-1}) + \frac{c}{1+c} E_t \left[\frac{1}{1+c}(p_{t+1}^* - z_t) + \frac{c}{1+c} \Delta z_{t+2} \right]$$

$$\Delta z_t = \frac{1}{1+c}(p_t^* - z_{t-1}) + \frac{c}{(1+c)^2} E_t(p_{t+1}^* - z_t) + \left(\frac{c}{1+c} \right)^2 E_t \Delta z_{t+2}$$

Or, repeating it into infinity:

$$\Delta z_t = \frac{1}{1+c} \sum_{k=0}^{\infty} \left(\frac{c}{1+c} \right)^k E_t(p_{t+k}^* - z_{t+k-1})$$

With $c > 0$, $\lim_{k \to \infty} \frac{1}{1+c} \sum_{k=0}^{\infty} \left(\frac{c}{1+c} \right)^k = 1$, so this representation is a geometrically decreasing weighting scheme where the current price change is determined by the current and all future weighted expected deviations of desired price from the past set price.