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The New Keynesian Phillips Curve with Myopic Agents

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The New Keynesian Phillips Curve with Myopic Agents

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Andreas Orland and Michael W.M. Roos¹

The New Keynesian Phillips Curve with Myopic Agents

Abstract

Empirical estimations of the New Keynesian Phillips curve support hybrid versions with a positive weight on lagged inflation and a weight less than one on expected inflation. We argue that myopic price setting of some agents explains the low weight on expected inflation. The lagged term can be explained by trend extrapolation if information about the future is costly. In a laboratory experiment we implement the Calvo (1983) microfoundations of the Phillips curve. Both of our hypotheses are supported by the experimental data. About half of the subjects set optimal Calvo prices while about a third is myopic.

JEL Classification: C91, D92, E52

Keywords: Hybrid Phillips curve; experimental economics; myopia; behavioral macroeconomics

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1 INTRODUCTION

In modern monetary macroeconomic models monetary policy has an effect on output because of the New Keynesian Phillips curve (NKPC). In its pure version the NKPC derived from theoretical models is forward-looking in the sense that current inflation depends on currently 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 due to discounting). In empirical studies, however, the estimated coefficient of expected inflation is often much smaller than one (e.g. Fuhrer [1], Galí and Gertler [2], Rudd and Whelan [3], Lindé [4], Schorfheide [5]) 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. [6], Dufour et al. [7], Nason and Smith [8], Hall et al. [9]).

The size of the weights of past and expected future inflation 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 [10] and Mankiw [11]. The purely backward-looking Phillips curve has also implausible properties as it predicts oscillatory dynamics.

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 (one is given by Galí and Gertler [2]: only a fraction of firms might be forward-looking, the other firms use lagged information to set their prices). Similarly, it is hard to explain why the weight on expected future inflation should be less than one. Indexation can be a reason why agents do not look into the future to make decisions, but stick to current information (e.g. Barro [12], Gray [13]).

In this paper, we suggest that boundedly rational behavior may be a reason for why empirical studies find weights greater than zero on lagged inflation and smaller than one on future expected inflation. We use the Calvo [14] microfoundations of the NKPC and implement them in a laboratory experiment. In the experiment we observe how subjects set prices in the Calvo setting and test whether their behavior can be described by full intertemporal optimization, which leads to the pure NKPC, or by heuristic behavior. If at least some subjects are myopic in the sense that they put too much weight on current relative to future information, the resulting Phillips curve has a weight of less than unity on expected inflation. Such a myopic bias at the aggregate level could either arise because all subjects fail to find the optimal price or because a fraction of price-setters uses simple rules-of-thumb while the others optimize. The idea that agents, especially households, use rules-of-thumb when making intertemporal decisions is well established in macroeconomics (see Campbell and Mankiw [15, 16]; Krusell and Smith [17]). In contrast to Galí and Gertler [2] who introduce rule-of-thumb behavior to explain a backward-looking term in the hybrid Phillips curve, we propose that it may also affect the forward-looking term.

It is often argued that the Calvo setting, in which firms receive random opportunities to reset their price is highly unrealistic from a behavioral point of view and that the main justification of that approach is its analytical convenience. Many macroeconomists

would consider it as an analytical shortcut for some more complicated story such as costly price adjustment (as modeled by Rotemberg [18]). While we do not want to make a strong case for the Calvo setting, it may not be as unrealistic as it first appears. Firms may be reluctant to adjust prices in existing relationships with customers and prefer to set new prices if they face new customers. The arrival of new customers, in turn, may be a random process from the perspective of the firm. Two more practical reasons for why we chose the Calvo setting are its enormous popularity in the literature and the ease which it can be implemented in the laboratory experiment. As we will show in Section 2 and Section 3 the Calvo model is a relatively simple intertemporal optimization setting that makes clear predictions of what optimizing subjects should do.

The use of laboratory experiments to study macroeconomic issues has become more and more popular (see Matheny and Noussair [19]; Lei and Noussair [20]; Fehr and Tyran [21, 22, 23]; Heinemann et al. [24, 25]; Duffy and Crocket [26]; see Duffy [27] for a survey). In a lab experiment it is possible to implement the stylized Calvo setting in a way that is close to theory which allows us to test the theory very directly. In contrast to econometric work with field data estimation issues are less of a problem. Furthermore all factors relevant for decision making can be isolated and we have control over the information set of subjects. Uncertainty and expectation formation which are notorious problems in studies using field data can be eliminated in the lab. Finally, we can observe individual behavior directly which allows us to analyze whether there are different types of subjects such as forward-looking and myopic ones.

2 THEORY AND RESEARCH QUESTIONS

The New Keynesian Phillips curve in its pure version¹ is

$$(1) \quad \pi_t = E_t \pi_{t+1} + \gamma \tilde{y}_t,$$

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 one:

$$(2) \quad \pi_t = \beta^f E_t \pi_{t+1} + \beta^b \pi_{t-1} + \gamma \tilde{y}_t \text{ with } 0 < \beta^f, \beta^b \leq 1.$$

Schorfheide [5] surveys the empirical literature of DSGE-model based estimations of the coefficients. The coefficients on lagged inflation range between .72 and 0, the coefficients on future inflation between 0 and 1, depending on estimation method, sample period and proxy for the output gap used.

Roberts [28] derives the Phillips curve in a discrete time version of the original model by Calvo [14]. Firms are price setters in a monopolistic competition framework. The central assumption is that in each period, only a fraction θ of the continuum of firms can reset the price. This is equivalent to the assumption that in each period, each firm has a probability of θ of being able to set a new price.

A firm's desired price p^* in each period t that would maximize profits is

$$(3) \quad p_t^* = p_t + \alpha \tilde{y}_t,$$

which depends on the overall price level p_t and the output gap \tilde{y}_t . Such a desired price follows from the monopolistic competition in the market.

¹ Other versions of the NKPC contain a discount factor. With quarterly data and the low inflation rates experienced in the last decades this coefficient is not one, but very close to it. We omit the coefficient therefore in our definition here.

With the Calvo assumption, a firm is stuck with a price set in the past when it cannot set a new price. When a firm gets the chance to reset the price, it must take into account that it will take some time before a new price can be chosen. This means that a rational firm must anticipate future desired prices and try to set a price such that deviations from desired prices in the current period and in the future are minimized. Hence the firm has to solve an intertemporal profit maximization problem. Rotemberg [18, 29] shows that with a quadratic approximation of the profit function around the equilibrium path the profit maximizing price is

$$(4) \quad z_t^* = \theta E_t \sum_{j=0}^{\infty} (1 - \theta)^j p_{t+j}^*.$$

This optimal price z_t^* is a weighted sum of the currently desired price and all expected future desired prices. The weighting scheme is a geometric series of the probability of not being able to reset the price in a given period, $1 - \theta$. Together with the fact that the overall price level is the weighted sum of all prices set in the present and past, the optimal pricing formula implies the New Keynesian Phillips curve (1).

Equation (4) is the central behavioral prediction of the Calvo model that we are going to test experimentally. The optimal Calvo price z_t^* is the solution of an intertemporal profit maximization problem and requires that subjects are forward looking and fully rational. We want to analyze whether subjects' behavior can be described by this rather sophisticated price-setting rule or whether simple heuristics describe their behavior better.

A simple heuristic subjects might use is to set the desired price of the current period

$$(5) \quad z_t^h = p_t^*.$$

Such a subject would be totally myopic as she disregards all future information. Nevertheless, this “fast and frugal heuristic” (Gigerenzer et al. [30]) is not unreasonable if future desired prices are unpredictable or very costly to predict. Furthermore if p_t^* enters the optimal price with the highest weight and the price stickiness is low, i.e. θ is high, the difference between z_t^h and the optimal price is small.

Another form of boundedly rational behavior might be partial myopia. In our case it means that agents on average use the correct form of the *weighting scheme* implied by the Calvo model, but are (slightly) myopic in the sense that they overestimate the true price setting probability of θ and therefore use wrong *weights*. Then firms would use a weight $\varphi > \theta$ to calculate the prices they intend to set so that their price-setting is described by:

$$(6) \quad z_t^m = \varphi \tilde{E}_t \sum_{j=0}^{\infty} (1 - \varphi)^j p_{t+j}^*$$

This behavior would imply the following Phillips curve²:

$$(7) \quad \pi_t^m = \frac{1-\varphi}{1-\theta} \tilde{E}_t \pi_{t+1} + \delta \tilde{y}_t,$$

With myopic behavior, it holds that $\frac{1-\varphi}{1-\theta} < 1$. The more weight subjects put on present information (the larger φ), the less inflation depends on expected future inflation. Boundedly rational behavior could hence explain the empirically observed coefficient of expected inflation. Note that (5) is a special case of (6) with $\varphi=1$. If all subjects are totally myopic, expected future inflation drops out of the Phillips curve.

Our research questions we want to answer in our experimental approach are:

² In a strict sense, expectations cannot be rational in this Phillips curve as subjects do not realize that they are myopic. We indicate this by the modified expectations operator.

1. Can subjects' average price-setting behavior be described by the Calvo model?

Equation (4) allows us to calculate the weights that subjects put on current and future information. We estimate the weights for all treatments and compare them with theoretical predictions. The predictive power of equation (4) can also be tested by variations of the price stickiness parameter θ . If the comparative statics of the model work subjects should put less weight on future prices if θ increases.

2. Is there myopic behavior?

As explained before, myopic behavior might reduce the size of the coefficient on expected inflation in the NKPC. We analyze whether price setting displays myopia in the aggregate and if so, whether this is caused by myopia of all subjects or only of some. A related question is how far subjects look into the future when they make their decision.

3. Do subjects use past information?

If subjects look backwards and use past information to determine their newly set price, they generate persistence in aggregate inflation as shown in Galí and Gertler [2]. A reason for using past information might be that future information is more costly to acquire which is realistic to assume. But lower information costs alone should not be a sufficient reason to use past data. It is only rational to use past data if it can be expected to have some predictive power for the future which would be the case if there is a trend in the data. We hence study the effects of both predictive power of past desired prices and acquisition costs of future desired prices on price setting.

3 EXPERIMENTAL DESIGN AND PROCEDURE

We implemented the theoretical model as closely as possible in the lab by generating a Calvo situation with random price setting opportunities for subjects. The experiment was framed in neutral terms with “prices” being called “values”, but we use the price setting terminology here for the ease of the exposition.

The experiment was an individual choice experiment in which subjects were paid according to their accumulated period profits over 105 periods. Both equations below were shown to subjects in the instructions. The profit per period³

$$(8) \quad \Pi_t = \max[0; 1,000 - Loss_t]$$

is a function of the losses caused by the price stickiness

$$(9) \quad Loss_t = 2.5[z_{t|t-j} - p_t^*]^2.$$

These losses in each period t are the quadratic deviations of the price $z_{t|t-j}$, which was set in period $t-j$ when the subject last had the opportunity to do so and could not yet be reset, and the desired price p_t^* .

Our aim is to find out how subjects set prices in an intertemporal setting. While the formation of expectations is an interesting topic of itself, we do not want the formation of expectations to interfere with price-setting decisions. It is exactly one of the great advantages of an experiment that we can eliminate the effects of confounding factors. In order to eliminate any complications resulting from the formation of expectations about desired prices (or even worse, two variables – output gap and overall price level), we provided subjects with all desired prices in the future, i.e. $E_t p_{t+j}^* = p_{t+j}^*$.

³ We limit minimal profits to zero in order to keep the experiment incentive compatible through the whole experiment. With a quadratic loss function losses incurred can be so huge that mistakes in the beginning of the experiment cannot be recovered during the experiment.

The experiment was implemented using z-Tree (Fischbacher [31]) (screen shots are supplied in the appendix). We had one benchmark session and six treatments, in which we vary the price setting probability θ , the availability and cost of the desired prices, and the stationarity of the desired prices (see Table 1).

Table 1: Summary of treatments

	No trend			Trend		
	Free Information	Costly Information		Free Information	Costly Information	
		Only Effort	Effort and Money		Only Effort	Effort and Money
$\theta=0.3$	Benchmark (20)	Treatment 2 (15)		Treatment 3 (16)	Treatment 4 (17)	Treatment 6 (25)
$\theta=0.3$ and $\theta=0.7$	Treatment 1 (49)		Treatment 5 (22)			

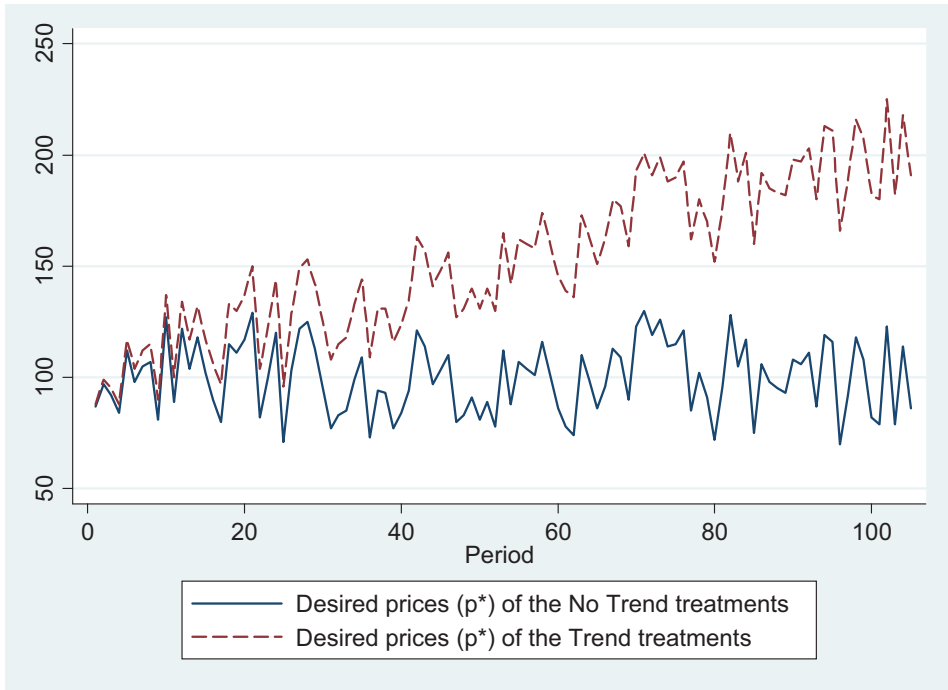
Notes: Trend/No Trend refers to the stationarity of the desired prices provided in a table on screen, Free Information/Costly Information without costs refers to the availability of the desired prices, Effort and Money/Effort refers to the type of the information cost. The number of subjects is shown in parentheses.

The benchmark session allows a general assessment of the predictive power of equation (4). The variation of θ in treatments 1 and 5 aims at the comparative statics of the model. In treatments 2, 4, 5, and 6 subjects must incur some costs to acquire future desired prices while current and past desired prices are freely available. These treatments have two functions. First, we can observe which information subjects actively acquire. Second, we can test whether subjects use freely available past information when future information is costly. The trend in treatments 3, 4, and 6 makes myopic behavior more costly, but at same time makes past desired prices informative about future ones.

In the benchmark session and in treatments 1 and 3, subjects saw a table of all desired prices of all periods.⁴ This table did not change during the session, but in each period the currently desired price was highlighted in blue while all the other prices were green. The desired prices were random draws from a uniform distribution on $[70, 130]$ with a mean of 99.9 and were equal for all subjects as the number had been drawn before the experiment (Figure 1 displays the time series of desired prices for all treatments). Subjects were not informed about the distribution the prices were drawn from. Below the table, subjects were informed about the price setting probability θ , which was kept constant at 0.3 in the benchmark session. When the random generator individually for each subject allowed the price to be reset in a period, subjects received an input field on the screen. The standard windows calculator could be activated. Inputs were allowed in the range $[0; 1,000]$ and had to be confirmed by a click on a button. If no price setting was possible, the input field was not displayed. In this case subjects could not do anything apart from looking at past periods' information and ending the period by pressing the button. At the bottom of the screen, the program displayed a history table with the desired prices in the past periods, the probability θ , whether a price was set in a period, the price set and the loss and profit for each past period. There was no feedback about the optimal price z_t^* or how much the set price deviated from it.

⁴ Before this experiment, we ran a pilot of the Calvo model with fixed and known intervals (two and five periods) for which the price is fixed. Here it is profit-maximizing to set the average of the desired prices of that interval. Almost all subjects set prices according to rule. As a consequence, we continued our work with this more demanding task.

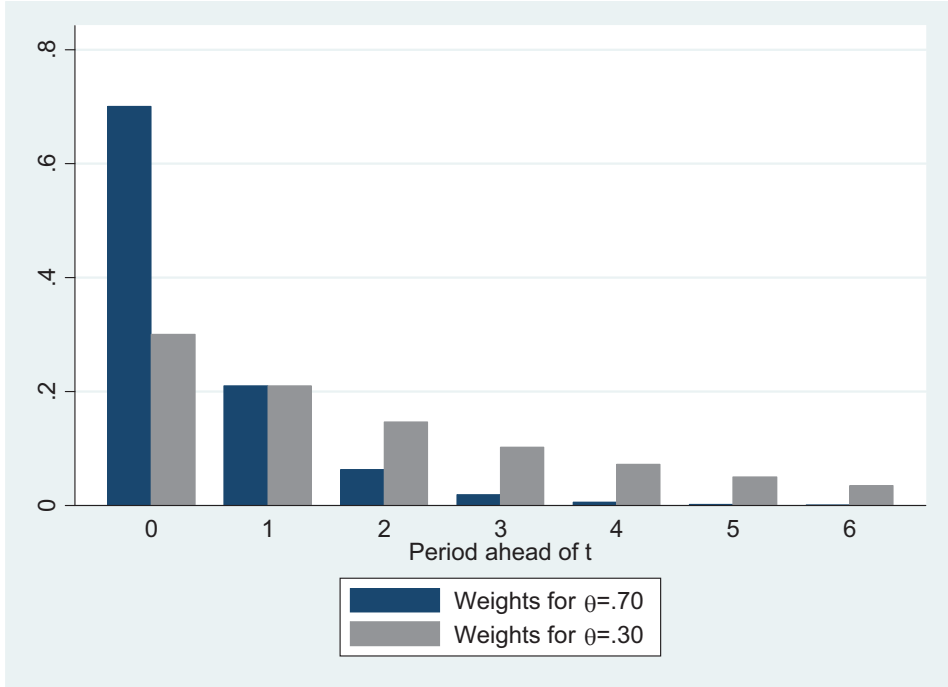
Figure 1: Time series of desired prices with and without trend



Since the optimal price crucially depends on the probability to get a price setting opportunity, we vary the probability ($\theta=0.3$ and $\theta=0.7$) in treatment 1 and treatment 5. The low θ of 0.3 implies that a firm is stuck with a price for 3.3 periods on average. With $\theta=0.7$ the average duration of fixed prices is 1.4 periods. This means that subjects should put more weight on future prices in the treatment with the lower θ than in the one in which θ is higher. Figure 2 displays the weights that equation (4) implies for both probabilities. We test whether subjects adjust their behavior in the implied way in a within-subject design by changing θ in the middle of the session in period 53. The period in which a change could occur was not announced, though in the instructions a change of probability was described as possible. The change was only shown on the computer screen, where θ was displayed in every period. To check for a potential order effect, we

reversed the order of high and low θ in two different sessions, but did not find any significant differences so that we pool the data in the empirical analyses.⁵

Figure 2: Theoretical weights implied by the probabilities used



A second change to the benchmark case is that we hid all future desired prices in the table on screen in treatment 5 and treatment 6. Only the desired prices in or before the current period t were automatically displayed. Subjects could obtain the future optimal prices p_{t+j}^* by clicking on the respective field in the table. For each click a cost of 10 points was charged (equivalent to one third of a euro cent), so that it required both effort and monetary costs to acquire information about the future. After a period was finished, future information disappeared again, so subjects had to pay twice or more often for prices that they wished to be revealed again. The motivation for these

⁵ We did not run sessions with $\theta=0.7$ only because the results for $\theta=0.3$ in treatment 1 and in the benchmark session were identical so that the within subject-design in treatments 1 and 5 is reliable.

treatments is that they allow us to observe directly which information subjects look at when they set their price and compare behavior of relatively informed subjects with subjects that access less information. Theoretically, it would be optimal to consider all future desired prices, but the weights in the Calvo formula (4) decline quickly, so that the practice of only looking at the first leads of the desired price is a relatively good approximation. Furthermore, subjects' behavior might change if they have to pay for information even if the cost is low.

In treatments 3 and 6 we added a linear time trend with a coefficient of 1 to the time series of desired prices. In both treatments 3 and 4, θ was fixed to 0.3 so that the weights given to the desired prices should be the same as in the treatments without the trend. The trend makes it more costly to disregard future information so that myopic behavior will generate higher ex-ante losses than in the case with stationary desired prices. In treatment 6, information was costly with the same conditions as in treatment 5. In treatment 3, in which future desired prices are freely available, the use of past desired prices does not make sense, but in treatment 6 some subjects might exploit the information in past prices by extrapolating the trend into the future instead of acquiring costly future information.⁶

In treatments 2 and 4 the monetary cost to uncover future information was zero. In addition to the effort cost of clicking some buttons on the computer screen, which is relatively small, there is the cognitive cost associated with the question of how many future desired prices a subject should acquire. In the treatments with free information, subjects had to think about the use of information, too, so that the cognitive costs are

⁶ In principle it is possible to determine the optimal amount of information about the future that subjects should acquire, depending on the costs. However, this would require assumptions about subjects' expectations about the path of future desired prices. While this is interesting it would complicate the analysis without yielding much additional insights to our research questions. We consider it a strength of our experiment that we do not have to deal with the formation of expectations.

comparable. Assuming that the effort cost is negligible a comparison of treatments 2 and 4 with the benchmark and treatment 3 allows us to infer which information subjects actually use when all information is free. A comparison with treatments 5 and 6 isolates the effect of the monetary cost.

We conducted the experimental sessions in the RUBex laboratory at Ruhr University Bochum. 168 student subjects (the majority of them economics and management students) participated in the experiment that lasted approximately 90 minutes. 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 (a translation of an example is supplied in the appendix). In the instructions, we did not supply a formula for the optimal values (z_t^*), but we informed them about the probability q of not being able to set a new price during x periods for a given probability θ , which is $q(x) = (1 - \theta)^x$. The instructions also made clear that q is decreasing in x and the comprehensive questions (also in the appendix) asked the subjects to calculate qs for two different periods of time ahead. Before the start of the experiment, subjects also had to calculate several hypothetical payoffs of some examples. On average subjects earned 19.26 euros, plus a show-up fee of 4 euros.

4 RESULTS

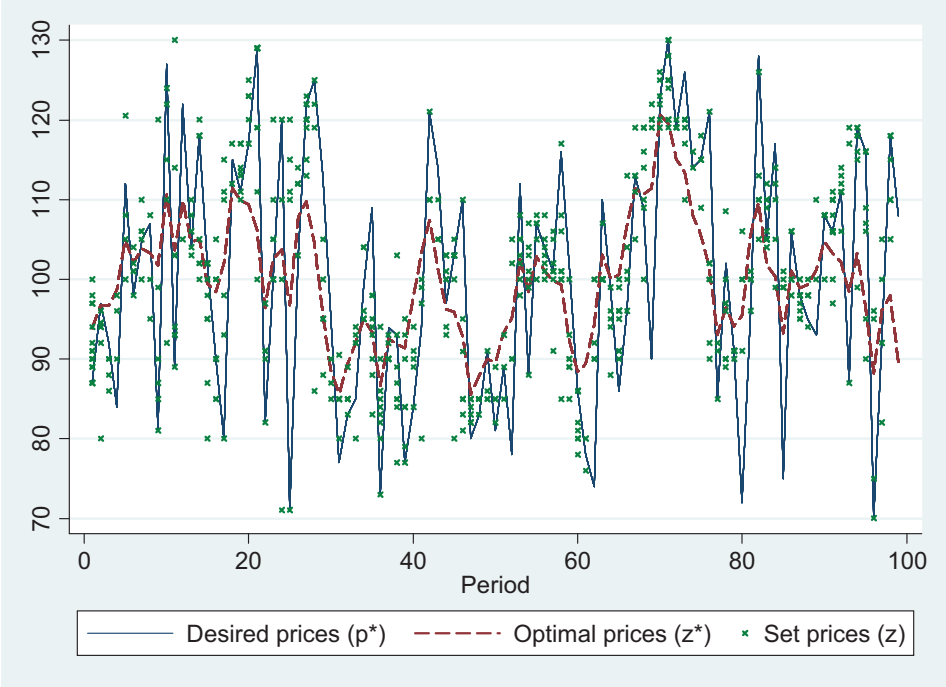
We present our experimental results in the order of our research questions. In the first subsection, we test whether the Calvo model predicts correctly how subjects set prices and how they respond to changes in the stickiness parameter θ . In the second subsection, we focus on the effects on information costs. This allows us to observe how much information subjects use and whether there are different types of subjects with

different degrees of future orientation. Finally, we analyze whether and under which conditions subjects use past data.

4.1 CALVO PREDICTIONS

Figure 3 shows the desired prices, the optimal prices computed with the Calvo formula (4) and prices set by subjects. As visible in the figure, prices set by subjects vary over time and follow the optimal price path quite closely. The correlation coefficient between set and optimal prices is $\rho=0.77$.

Figure 3: Optimal, desired and set prices in the benchmark treatment



Our main interest is whether our subjects are looking into the future and set prices as predicted by the Calvo formula (4). A direct test on whether the Calvo formula (4) is a

reasonable predictor of subjects' behavior is to regress⁷ the prices set on the desired prices of the current and future periods:

$$(10) \quad z_{it} = \beta_0 p_{it}^* + \beta_1 p_{it+1}^* + \beta_2 p_{it+2}^* + \beta_3 p_{it+3}^* + \beta_4 p_{it+4}^* + \beta_5 p_{it+5}^* + \beta_6 p_{it+6}^* + \varepsilon_{it}.$$

This regression reveals the implied weights that all subjects on average put on the respective prices. These weights can be compared with the theoretically predicted ones using t-tests and F-tests. Although the optimal price in principle depends on all future desired prices, we include only six leads in the regression because even the theoretical weights are fairly small after lead six. The results do not change substantially if we use fewer or more leads. All regressions pool the data within the respective treatments.⁸

Column (2) of Table 2 shows the estimated weights in the benchmark session and column (1) contains the theoretical weights. The fit of the regression is good and as a general result the estimated weights are not far away from the Calvo weights. This indicates that subjects actually used the provided information in a quite sensible way. The weights decline in a fashion similar to the one predicted and are not significantly different from zero after lead 4. Note that the first two weights are significantly larger than the Calvo weights so that on average subjects rely too much on information about the present and the near future relative to the theoretical model. The Wald test rejects that all estimated coefficients are equal to the theoretical parameters.

⁷ We estimated the equation by OLS with robust standard errors to account for heteroskedasticity. The last seven periods' observations were discarded because the finite time horizon biases the weights in the last periods. We used only those observations, in which a price was actually set (and use the shorthand notation z_{it} for $z_{it|t-j}$ for each individual i), and removed a few outliers which are defined as prices outside the interval of a priori reasonable prices of [70, 130] for prices without the trend; for prices with a trend the upper bound was 225 (which was never crossed). We ran two robustness checks: one with a lagged dependent variable as regressor and another one with lagged residuals to account for potential autocorrelation. They all produced practically identical results. These estimation details apply to all similar estimations in the paper. The appendix contains information about the discarded observations.

⁸ We ran regressions for three subsamples (periods 1-49, 11-49, 50-98) of the benchmark, treatment 3 and treatment 6 to check for learning. But for all treatments and subsamples Wald tests cannot reject equality. We cannot observe learning over time.

Subjects' behavior in the benchmark session can hence be approximated by the Calvo model, but on average subjects are slightly myopic.

Table 2: Estimated weights of the desired prices with $\theta=0.3$

Dependent variable: z_{it}	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\theta(1-\theta)^j$	Benchmark	Treatment 1	Treatment 2	Treatment 3	Treatment 4	Treatment 5	Treatment 6
			Free Information	Buttons w/o Costs	Free Information Trend	Buttons w/o Costs Trend	Buttons & Costs	Buttons & Costs Trend
p_{it}^*	.3	.460** (.026)	.502** (.021)	.459** (.031)	<i>.354**</i> (.027)	.472** (.035)	.496** (.035)	.497** (.032)
p_{it+1}^*	.21	.278** (.025)	.261** (.019)	<i>.265**</i> (.031)	<i>.210**</i> (.028)	<i>.186**</i> (.031)	<i>.220**</i> (.034)	<i>.169**</i> (.029)
p_{it+2}^*	.147	<i>.135**</i> (.020)	<i>.136**</i> (.017)	<i>.115**</i> (.026)	.238** (.024)	<i>.075*</i> (.092)	<i>.104**</i> (.033)	<i>.087**</i> (.033)
p_{it+3}^*	.103	<i>.091**</i> (.021)	.053** (.017)	<i>.075*</i> (.032)	<i>.138**</i> (.024)	<i>.092*</i> (.038)	<i>.110**</i> (.031)	<i>.123**</i> (.033)
p_{it+4}^*	.072	<i>.057**</i> (.020)	.018 (.016)	<i>.083**</i> (.029)	<i>.053**</i> (.022)	<i>.067</i> (.035)	<i>.092**</i> (.029)	<i>.029</i> (.029)
p_{it+5}^*	.051	-.031 (.018)	-.019 (.014)	<i>.017</i> (.023)	<i>.014</i> (.022)	<i>.065*</i> (.027)	<i>.020</i> (.027)	<i>.035</i> (.027)
p_{it+6}^*	.035	<i>.017</i> (.018)	<i>.047**</i> (.017)	<i>-.014</i> (.026)	<i>-.003</i> (.023)	<i>.036</i> (.027)	<i>-.041</i> (.027)	<i>.056</i> (.023)
Pseudo R ²		.655	.670	.571	.956	.848	.601	.871
#		560	785	441	401	505	351	742
Significance level of Wald test on equality of all coefficients with regression in:								
Column (1)		.00	.00	.00	.00	.00	.00	.00
Column (2)		-	.23	.46	.00	.00	.18	.00
Column (3)		.23	-	.21	.00	.00	.02	.01
Column (4)		.46	.21	-	.00	.16	.93	.04
Column (5)		.00	.00	.00	-	.00	.00	.00
Column (6)		.00	.00	.16	.00	-	.21	.89
Column (7)		.18	.02	.93	.00	.21	-	.09
Column (8)		.00	.01	.04	.00	.89	.09	-

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, $\theta(1-\theta)^j$ theoretical weight for lead j , robust standard errors in parentheses

Table 3: Estimated weights of the desired prices with $\theta=0.7$

Dependent variable: z_{it}	(1)	(2)	(3)
	$\theta(1-\theta)^j$	Treatment 1 Free Information	Treatment 5 Buttons and Costs
p_{it}^*	.7	.774** (.011)	.780** (.021)
p_{it+1}^*	.21	.159** (.020)	.167** (.023)
p_{it+2}^*	.063	.051** (.008)	.038** (.014)
p_{it+3}^*	.019	<i>.002</i> (.009)	.015 (.018)
p_{it+4}^*	.006	-.010 (.009)	.002 (.017)
p_{it+5}^*	.002	.006 (.008)	-.014 (.013)
p_{it+6}^*	.001	.015* (.008)	.015 (.014)
Pseudo R ²		.842	.776
#		1651	731
Significance level of Wald test on equality of all coefficients with regression in:			
Column (1)		.00	.00
Column (2)		-	.40
Column (3)		.40	-

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, $\theta(1-\theta)^j$ theoretical weight for lead j , robust standard errors in parentheses

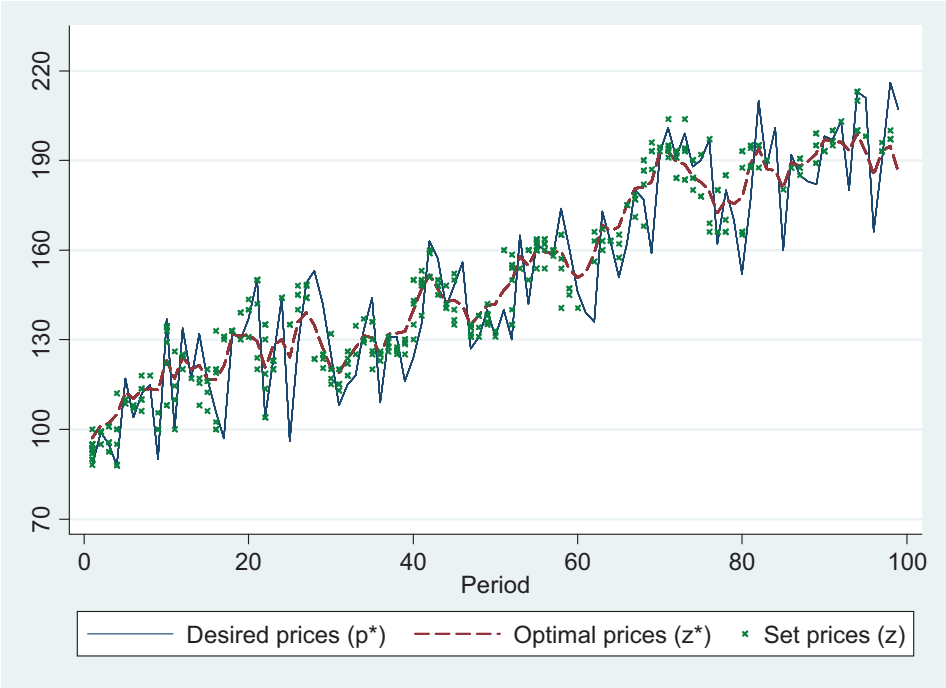
In treatments 1 and 5 the estimated weights for $\theta=0.3$ display similar properties to the ones in the benchmark session (compare columns (3) and (7) of Table 2 with the baseline treatment in column (2)). In a Wald test, we cannot reject the null hypothesis of equality of the two estimations with the estimations for the baseline treatment. This similarity indicates that the prior knowledge that θ might change does not influence behavior.

Table 3 shows the estimates for the periods in which $\theta=0.7$ held in treatments 1 and 5. The theoretically predicted weighting scheme puts a higher weight on p_{it}^* and lower weights on all leads after p_{it+1}^* than with $\theta=0.3$. This pattern is actually found in both

treatments (Wald tests, $p=0.000$). In fact, the estimated weights are not significantly different from zero after lead 2. Again the estimated coefficient of β_0 is larger than theoretically expected, but now β_1 is too low. We can conclude that subjects respond to changes in the stickiness parameter in a way that is consistent with the Calvo model.

Figure 4 shows the optimal and set prices in treatment 3 in which the desired priced are trended. The correlation coefficient between set and optimal prices is $\rho=0.97$. This is higher than in the previous treatments indicating that subjects' behavior in the setting with non-stationary desired prices is more forward-looking and thus closer to the theoretically predicted behavior.

Figure 4: Optimal, desired and set prices in treatment 3



The estimated weights in Table 2, column (5), are still significantly different from the theoretical weights, but the coefficient β_0 for the current period and next periods'

desired prices β_1 are much closer to the predictions than in the benchmark session. β_0 is still too high, but with a time trend, subjects seem to pay more attention to the desired prices in the more distant future. One explanation is that myopic behavior is more costly if general economic conditions change over time.

4.2 INFORMATION COSTS AND USE OF INFORMATION

When information costs consist only of effort costs in treatment 2 the estimated weights are not different from the benchmark (see Table 2, column (4)). This suggests that on average prices were set in the same way in both groups.

For each subject we calculate the average number of desired future prices acquired per period in which a price could be set, n_i . Table 4 shows that the mean of n_i over all subjects in treatment 2 is 3.73, which is close to the expected duration of not being able to set a new price for $\theta=0.3$ (3.33). On average subjects acquired about 4 future desired prices if there is just an effort cost⁹. We might hence conclude that subjects also use about for leads of the desired prices in the sessions with free information.

⁹ In principle subjects could have acquired all future information in the first periods by clicking on all buttons and taking notes. But no subject did this. The maximum number of future desired prices acquired in one period was 31. In general, subjects acquired about the same number of future prices in every price setting period.

Table 4: Mean ratios of acquired future prices to set prices

			<i>All subjects</i>	<i>Median</i>	<i>Ignorant subjects</i>	<i>Informed subjects</i>
Treatment 2	No Monetary	$\theta=0.3$	3.73	3.77	2.03	5.44
	Cost,				[0; 11]	[0; 19]
	No Trend					
Treatment 4	No Monetary	$\theta=0.3$	3.31	3.90	1.37	5.19
	Cost, Trend				[0; 20]	[0; 31]
Treatment 5	Monetary	$\theta=0.3$	1.49	1.08	0.64	2.34
	Cost,				[0; 4]	[0; 15]
	No Trend					
		$\theta=0.7$	0.74	1.08	0.30	1.19
					[0; 3]	[0; 13]
Treatment 6	Monetary	$\theta=0.3$	1.55	1.60	0.50	2.59
	Cost, Trend				[0; 7]	[0; 12]

Notes: The table gives the mean ratios for all subjects and for subjects that acquired more information than the median subject (the informed subjects) and less information (the ignorant). Numbers in brackets the minimum and maximum number of periods a subject looked up.

We can use the average number of uncovered future prices per subject and period, n_i , to classify subjects as “informed” or “ignorant”. Informed subjects are those with n_i above the median, ignorant ones below. Table 4 shows that the informed subjects in treatment 2 on average acquired 5.44 future prices whereas the ignorant ones uncovered only 2.03. In treatment 4 with a trend the difference is much larger, 5.19 vs. 1.37, while the overall mean and median are similar to treatment 2. Interestingly, the estimated weights in treatment 4 with a trend are statistically not different from those in treatment 2 (see Table 2 columns (6) and (4)).

It is obvious to ask if the differences in the acquisition of information between ignorant and informed subjects result in different price setting behavior. Table 5 shows that in treatment 2, in which the average informed subject acquired about 2.5 time as many future prices per period as the average ignorant subject, the estimated weight do not

differ statistically (Wald test, $p=0.51$). In contrast, the estimated weights differ significantly between the two groups in treatment 4, in which the weights of the informed subjects are close to the Calvo predictions whereas the ignorant subjects are highly myopic. An interpretation of the findings in Tables 4 and 5 is that with stationary data, many of the subjects that acquired an above-median amount of information did not know how to use this information and only acquired it because the effort cost was low and the freely available data was not informative. With the trend in treatment 4, however, this type of subjects had an alternative source of information available and refrained from uncovering future information as they did not know how to use it anyway.

The additional monetary cost of 10 points in treatments 5 and 6 clearly reduced subjects' willingness to acquire information as visible in Table 4. The average number of uncovered prices is less than half compared to treatments 2 and 4. In treatment 5 there were two subjects did not acquire information at all. Still for all subjects the estimated weights in the treatments without trend do not differ from the respective benchmarks (see Tables 2 and 3).

With monetary costs the estimated weights significantly differ between informed and ignorant subjects in both treatments (see Table 6). With $\theta=0.7$ in treatment 5, informed subjects set Calvo prices, with $\theta=0.3$ the weights were different from the Calvo weights but close. Ignorant subjects, however, were clearly myopic, putting high weights on the desired price of the current period and the first lead and almost no weight on leads 2 and higher. Monetary costs of information hence allow us to separate different types of subjects more clearly than pure effort costs.

Table 5: Estimated weights of the desired prices of informed and ignorant subjects in treatments 2 and 4

Dependent variable: z_{it}	<i>Treatment 2</i>			<i>Treatment 4</i>	
		No trend		Trend	
	(1)	(2)	(3)	(4)	(5)
	$\theta(1-\theta)^j$	informed	ignorant	informed	ignorant
p_{it}^*	.3	.432** (.039)	.489** (.049)	.301** (.051)	.625** (.047)
p_{it+1}^*	.21	.296** (.036)	.232** (.058)	.262** (.041)	.124** (.044)
p_{it+2}^*	.147	.141** (.033)	.083 (.043)	.093 (.048)	.069 (.044)
p_{it+3}^*	.103	<i>.021</i> (.036)	.120* (.054)	.217** (.057)	<i>-.008</i> (.053)
p_{it+4}^*	.072	.085* (.034)	.083 (.049)	.062 (.051)	.021 (.046)
p_{it+5}^*	.051	.014 (.029)	.028 (.039)	.064 (.037)	.087* (.041)
p_{it+6}^*	.035	.015 (.034)	<i>-.040</i> (.039)	.002 (.036)	.063 (.041)
Pseudo R ²		.66	.52	.84	.88
#		203	205	232	244

Significance level of Wald test on equality of all coefficients with regression in:

Column (1)	.00	.00	.00	.00
Column (2)	-	.51	.12	.04
Column (3)	.51	-	.00	.04
Column (4)	.02	.12	-	.00
Column (5)	.00	.04	.00	-
Table 2, column (2)	.38	.31	.00	.00
Table 2, column (3)	.15	.34	.00	.00
Table 2, column (4)	.47	.59	.04	.00
Table 2, column (5)	.01	.01	.16	.00
Table 2, column (6)	.07	.58	.00	.00
Table 2, column (7)	.24	.99	.02	.01
Table 2, column (8)	.01	.34	.08	.01
Table 5, column (2)	.30	.16	.12	.00
Table 5, column (3)	.00	.09	.00	.74
Table 7, column (2)	.07	.09	.87	.00
Table 7, column (3)	.00	.01	.00	.80

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, $\theta(1-\theta)^j$ theoretical weight for lead j , robust standard errors in parentheses

Table 6: Estimated weights of the desired prices of informed and ignorant subjects in treatments 5 and 6

Dependent variable:	Treatment 5						Treatment 6	
	$\theta=0.3$			$\theta=0.7$			$\theta=0.3$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Z_{it}								
	$\theta(1-\theta)^j$	informed	ignorant	$\theta(1-\theta)^j$	informed	ignorant	informed	ignorant
p_{it}^*	.3	.349** (.040)	.682** (.044)	.7	.704** (.034)	.851** (.026)	.336** (.042)	.636** (.048)
p_{it+1}^*	.21	.322** (.048)	<i>.089*</i> (.045)	.21	.235** (.035)	.104** (.028)	.258** (.037)	.084 (.046)
p_{it+2}^*	.147	.138** (.038)	<i>.089*</i> (.044)	.063	.030 (.024)	<i>.048**</i> (.016)	.143** (.048)	<i>.034</i> (.046)
p_{it+3}^*	.103	.148** (.039)	<i>.012</i> (.040)	.019	.022 (.029)	.009 (.020)	.199** (.047)	.059 (.046)
p_{it+4}^*	.072	.091** (.031)	.069 (.048)	.006	.021 (.026)	-.013 (.021)	.059 (.043)	.047 (.036)
p_{it+5}^*	.051	.035 (.031)	.024 (.040)	.002	-.024 (.020)	-.016 (.018)	.006 (.039)	.038 (.036)
p_{it+6}^*	.035	-.072* (.036)	.006 (.033)	.001	.015 (.021)	.018 (.017)	.003 (.032)	.085** (.032)
Pseudo R ²		.640	.680		.733	.832	.876	.882
#		196	155		363	368	351	369
Significance level of Wald test on equality of all coefficients with regression in:								
Column (1)		.00	.00		-	-	.00	.00
Column (2)		-	.00		-	-	.38	.00
Column (3)		.00	-		-	-	.00	.58
Column (4)		-	-		.29	.00	-	-
Column (5)		-	-		-	.03	-	-
Column (6)		-	-		.03	-	-	-
Column (7)		.38	.00		-	-	-	.00
Column (8)		.00	.58		-	-	.00	-
Table 2, column (2)		.09	.00		-	-	.05	.00
Table 2, column (3)		.00	.00		-	-	.00	.00
Table 2, column (4)		.24	.00		-	-	.06	.00
Table 2, column (5)		.08	.00		-	-	.64	.00
Table 2, column (6)		.00	.01		-	-	.01	.05
Table 2, column (7)		.00	.00		-	-	.03	.00
Table 2, column (8)		.00	.00		-	-	.00	.00
Table 3, column (2)		-	-		.07	.07	-	-
Table 3, column (3)		-	-		.04	.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, $\theta(1-\theta)^j$ theoretical weight for lead j , robust standard errors in parentheses

We conclude from this section that there are indeed different types of subjects, forward-looking and myopic ones. The forward-looking subjects consider about five future periods when there is only the effort cost. With monetary costs they look about 2.5 periods into the future. The myopic types uncover no more than two desired prices in

the future without monetary costs and less than one future price on average if they have to pay. The information acquisition depends on the availability of alternative information like the one contained in a time trend and the cost of information.

There is a clear difference in the price setting behavior of informed and ignorant subjects. Informed subjects set prices that are very close to the prices predicted by the Calvo model, although their prices are slightly biased toward the present. Ignorant subjects are strongly myopic and set prices which are very close to the desired price of the current period.

The estimated weighting schemes for future information are very similar in all treatments if we estimate them with the observations from all subjects despite the differences between the types observed in the costly-information treatments. This finding suggests that the aggregate results in the treatments in which we cannot observe the use of information are also a mixture of prices set by ignorant and forward-looking subjects. We conclude that even if information is freely available, some subjects do not use it so that average prices in the aggregate are influenced by strongly myopic subjects.

4.3 BACKWARD-LOOKING BEHAVIOR

Persistence in the NKPC cannot result from myopic behavior but requires some kind of backward-looking behavior. We test for backward-looking behavior by regressing the price set on the current price, two lags lag of the desired price and the part of the theoretical price that results from the future desired prices¹⁰

$$(12) \quad z_{it} = \alpha_1 p_{it-1}^* + \alpha_2 p_{it-2}^* + \alpha_3 p_{it}^* + \alpha_4 (z_{it}^* - \theta p_{it}^*) + \varepsilon_{it}.$$

¹⁰ As in the previous regressions, only prices of the period in which they were set are considered ($z_{it|t-j}$ only for $j=0$), and only within the reasonable range. Last seven periods' prices are omitted.

If the theoretical Calvo price is an unbiased predictor of the price actually set, we should not be able to reject the null that $\alpha_1 = \alpha_2 = 0$, $\alpha_3 = \theta$ and $\alpha_4 = 1 - \theta$. This hypothesis is always rejected (F-test, $p < 0.01$, see Table 7) as α_3 is typically larger than θ .

The hypothesis that past desired prices do not explain the chosen price, $\alpha_1 = \alpha_2 = 0$, is rejected in 3 out of 9 cases (F-tests, $p < 0.05$). However, in treatment 1 the significantly positive coefficient on the second lag is small and may be a statistical artifact. The past clearly matters in treatments 4 and 6 in which desired prices had a time trend and future information was costly. The estimates of α_1 and α_2 are highly significant and comparatively large in both treatments. This finding supports our conjecture that some subjects use freely available past information if it has predictive power due to a time trend and future information is costly.

Table 7: Bias and backward-looking behavior

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent variable: z_{it}	Prediction	Benchmark	Treatment 1		Treatment 2	Treatment 3	Treatment 4	Treatment 5		Treatment 6
		$\theta=0.3$	$\theta=0.3$	$\theta=0.7$	$\theta=0.3$	$\theta=0.3$	$\theta=0.3$	$\theta=0.3$	$\theta=0.7$	$\theta=0.3$
p_{it-1}^*	0	.03 (.02)	-.01 (.02)	.01 (.01)	.04 (.03)	-.02 (.02)	.12** (.03)	-.01 (.03)	<i>.03*</i> (.02)	.12** (.03)
p_{it-2}^*	0	-.02 (.02)	.00 (.02)	<i>.02*</i> (.01)	-.01 (.02)	-.03 (.02)	<i>.05*</i> (.02)	-.02 (.03)	.00 (.01)	.06** (.02)
p_{it}^*	θ	.45** (.03)	.49** (.02)	.77** (.01)	<i>.33**</i> (.04)	<i>.36**</i> (.03)	<i>.34**</i> (.05)	.50** (.04)	.77** (.02)	<i>.29**</i> (.05)
$z_{it}^* - \theta p_{it}^*$	$1-\theta$	<i>.79**</i> (.05)	<i>.74**</i> (.04)	.70** (.04)	<i>.87**</i> (.07)	.98** (.05)	<i>.69**</i> (.08)	<i>.75**</i> (.07)	.69** (.08)	<i>.74**</i> (.07)
Pseudo R ²		.62	.64	.84	.53	.94	.89	.58	.34	.87
#		537	758	1,612	427	385	487	337	712	724
F-tests on joint differences of the following coefficients from predictions:										
All coefficients		.00	.00	.00	.00	.00	.00	.00	.00	.00
p_{it-1}^* and p_{it-2}^*		.32	.87	.01	.16	.16	.00	.56	.06	.00
p_{it}^* and $z_{it}^* - \theta p_{it}^*$.00	.00	.00	.00	.00	.45	.00	.00	.71

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

5 IMPLICATIONS FOR THE PHILLIPS CURVE AND INDIVIDUAL BEHAVIOR

We found that in the aggregate, the Calvo model can be used to describe subjects' price setting behavior, at least qualitatively, although they are slightly myopic on average. In equation (6) we assumed that subjects use a geometric weighting scheme to determine the price they set, but that they use a parameter φ that is greater than the probability θ . With this assume we can model myopic behavior because the resulting prices depend more on current information and less on future information than the Calvo prices.

We can use the estimated weights of Table 2 to determine the parameter φ which would generate geometric weights than are close to the estimated ones in the sense that the root mean squared error between the calculated weights and the estimated ones is minimized. Table 9 shows the estimated φ s for each treatment with $\theta=0.3$ in column (1) Column (3) shows that myopia can generate a Phillips curve coefficient on future inflation that is compatible with empirical estimates.

Table 9: Estimated stickiness parameters of all treatments with $\theta=0.3$

	(1)	(2)	(3)
	Estimated φ	RMSE	$\frac{1 - \varphi}{1 - \theta}$
Benchmark	.46	.02	.77
Treatment 1	.50	.02	.71
Treatment 2	.46	.02	.77
Treatment 3	.35	.04	.93
Treatment 4	.46	.04	.77
Treatment 5	.48	.04	.74
Treatment 6	.48	.05	.74

In the previous section, we reported evidence that some subjects are myopic while others are more forward-looking. For theoretical modeling it might be interesting to

know the proportion of Calvo and myopic types. We estimate a restricted version of equation (10) also for each individual subject by OLS:

$$(13) \quad z_t = \gamma_0 p_t^* + \gamma_1 (z_t^* - \theta p_t^*) + \varepsilon_t$$

Using an F-test we can test whether $\gamma_0 = \theta$ and $\gamma_1 = 1$. If this cannot be rejected, subjects are Calvo types in a statistical sense. If, on the contrary $\gamma_0 > \theta$ and $\gamma_1 < 1$, subjects are myopic and put too much weight on the present desired price. An extremely myopic individual would choose $\gamma_0 = 1$ and $\gamma_1 = 0$. Table 10 shows that 53.4 % of our subjects in all treatments can be classified as Calvo types and 35.6% are myopic. In the individual treatments these proportions are roughly similar so that we do not see any systematic impact of treatment conditions on the type classification.

Table 10: Classification of subjects in all treatments

Type	γ_0	γ_1	Total
Calvo	θ	1	87 (53.4%)
Myopic	$>\theta$	<1	58 (35.6%)
Other			18 (11.0%)

Notes: The table contains the number of subjects and the respective shares of the total number in the treatment for which the F-test did not reject the null (Calvo) or did do (Myopic/Others).

5 CONCLUSIONS

In our laboratory experiment we found that the optimal price equation in the Calvo [14] model describes the average price-setting behavior under ideal experimental conditions quite well. The estimate weights on future desired prices implied by the observed process decline geometrically with the time horizon and are close to the theoretically predicted weights. Furthermore, subjects set prices that are closer to the desired price in the current period, if price stickiness is lower, as predicted by the model.

Although subjects' chosen prices are on average close to the Calvo predictions, they are slightly biased towards to present in the sense that subjects put too much weight on the desired price of the period in which the new price is set. This bias results from a significant fraction of myopic individuals that neglect most of the available information about the future and often simply set a price close to the one that would be profit maximizing in the current period only. Among the participants of our experiment, the fraction of forward-looking Calvo types was about 53%, whereas the fraction of myopic subjects was roughly 36%. We argue that the empirically estimated coefficients on expected future inflation in the New Keynesian Phillips curve, which are often much smaller than the theoretical prediction of approximately one, can be explained by myopia.

Our results also offer an explanation to the puzzle why there is a significant lagged term in empirical estimations of the Phillips curve. We found that some subjects use past desired prices if they are freely available and future information is costly. However, they do this only if past observations have predictive power for the future, which is the case when the data has a time trend. With stationary data, when nothing can be learned from the past, historical information is not used.

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APPENDIX A

Figure A1: Screenshot of the z-Tree program

Periode 1 von 103 Verbleibende Zeit [sec] 26

Periode	1	2	3	4	5	6	7	8	9	10
Preis	87.0	97.0	92.0	94.0	112.0	90.0	105.0	107.0	91.0	127.0
Preis	11	12	13	14	15	16	17	18	19	20
Preis	89.0	122.0	108.0	116.0	102.0	90.0	90.0	119.0	111.0	117.0
Preis	21	22	23	24	25	26	27	28	29	30
Preis	129.0	131.0	133.0	135.0	137.0	139.0	141.0	143.0	145.0	147.0
Preis	21	22	23	24	25	26	27	28	29	30
Preis	77.0	77.0	80.0	80.0	80.0	73.0	84.0	92.0	77.0	84.0
Preis	41	42	43	44	45	46	47	48	49	50
Preis	84.0	84.0	84.0	84.0	84.0	84.0	84.0	84.0	84.0	84.0
Preis	51	52	53	54	55	56	57	58	59	60
Preis	82.0	82.0	82.0	82.0	82.0	82.0	82.0	82.0	82.0	82.0
Preis	61	62	63	64	65	66	67	68	69	70
Preis	70.0	70.0	70.0	70.0	70.0	70.0	70.0	70.0	70.0	70.0
Preis	71	72	73	74	75	76	77	78	79	80
Preis	120.0	120.0	120.0	120.0	120.0	120.0	120.0	120.0	120.0	120.0
Preis	81	82	83	84	85	86	87	88	89	90
Preis	80.0	120.0	105.0	117.0	75.0	106.0	90.0	95.0	82.0	108.0
Preis	91	92	93	94	95	96	97	98	99	100
Preis	100.0	111.0	97.0	119.0	119.0	70.0	82.0	119.0	100.0	97.0
Preis	101	102	103	104	105	106	107	108	109	110
Preis	100	100	100	100	100	100	100	100	100	100

Bitte setzen Sie Ihren Preis

Field to enter values

Calculator button

History of past periods

Figure A2: Screenshot of the z-Tree program with information cost

Periode 1 von 103 Verbleibende Zeit [sec] 24

Bestimmen Sie die Werte für die Perioden auf, die Sie sehen möchten, indem Sie auf die Buttons klicken:

87.0	97.0	92.0	94.0	112.0	90.0	105.0	107.0	91.0	127.0
11	12	13	14	15	16	17	18	19	20
89.0	122.0	108.0	116.0	102.0	90.0	90.0	119.0	111.0	117.0
21	22	23	24	25	26	27	28	29	30
129.0	131.0	133.0	135.0	137.0	139.0	141.0	143.0	145.0	147.0
21	22	23	24	25	26	27	28	29	30
77.0	77.0	80.0	80.0	80.0	73.0	84.0	92.0	77.0	84.0
41	42	43	44	45	46	47	48	49	50
84.0	84.0	84.0	84.0	84.0	84.0	84.0	84.0	84.0	84.0
51	52	53	54	55	56	57	58	59	60
82.0	82.0	82.0	82.0	82.0	82.0	82.0	82.0	82.0	82.0
61	62	63	64	65	66	67	68	69	70
70.0	70.0	70.0	70.0	70.0	70.0	70.0	70.0	70.0	70.0
71	72	73	74	75	76	77	78	79	80
120.0	120.0	120.0	120.0	120.0	120.0	120.0	120.0	120.0	120.0
81	82	83	84	85	86	87	88	89	90
80.0	120.0	105.0	117.0	75.0	106.0	90.0	95.0	82.0	108.0
91	92	93	94	95	96	97	98	99	100
100.0	111.0	97.0	119.0	119.0	70.0	82.0	119.0	100.0	97.0
101	102	103	104	105	106	107	108	109	110
100	100	100	100	100	100	100	100	100	100

Bitte setzen Sie Ihren Preis

Field to enter values

Calculator button

History of past periods

APPENDIX B

Instruction and comprehensive questions for Treatment 1 (original emphasis, note that what we call desired price is called optimal value in the instructions)

Instructions

Welcome to this experiment. Please do not talk to any other participant from now on. We kindly ask you to use only the functions of the computer that are necessary for the conduct of the experiment.

The purpose of this experiment is to study decision behavior. You can earn real money in this experiment. Your payment will be determined solely by your own decisions according to the rules on the following pages.

The data from the experiment will be anonymized and cannot be related to the identities of the participants. Neither other participants nor the experimenters will find out which choices **you** have made and how much **you** have earned during the experiment.

Rules of the experiment

Your task is to set **values**. The experiment will take 105 periods. You are setting a value in the first period. Thereafter, you will not be able to set a value in every subsequent period. It will be determined randomly by the computer whether or not you are allowed to set a new value. During each period you will receive a message about whether you are allowed to set a value or not. *As long as you are not allowed to set a new value, you have to stick to your previous value.* The **probability** p with that you are allowed to set a value will be shown in the beginning of the experiment and in each period. The probability in each period is equal to the value and independent of whether you were able or not to set a value in the previous periods. The probability p might change during the experiment and you will be informed about the new data.

The probability that you *cannot* set a value within the next x periods is labeled q :

$$q(x) = [1 - p]^x$$

Example: If p is 0.8 (so the probability is 80%), the probability q , that you *cannot* set a new value during the following three periods is:

$$q(3) = [1 - 0.8]^3 = 0.2 * 0.2 * 0.2 = 0.008 = 0.8\%$$

The probability q decreases with increasing number of periods x .

You will be given the **optimal value** for each period. To set it would be optimal *if you were able to reset your value in each period*. All optimal values will be shown in a table.

At most you can earn 1,000 points per period. Because the value is fixed and you cannot set the optimal value in each period, you recover a loss. This **loss** will be deducted from the maximum income of the period.

The following formula expresses the loss that will be deducted from your maximum income, depending on the optimal value:

$$\text{Loss of period} = 2.5 * [\text{set value} - \text{optimal value}]^2$$

Your **earning** depends on how much your set value deviates from the optimal value of the period. Both upwards and downwards deviations reduce your earnings. Here applies: the bigger the deviation, the bigger is the loss and bigger deviations affect losses *disproportionally*.

The following formula expresses the earning in dependence on loss:

$$\text{Earning of a period} = \text{Maximum (0; 1,000 - loss of period)}$$

This means that your earnings are at least zero. With losses that are bigger than 1,000 you will not achieve negative earnings.

Enter the value in a field on the display. You can determine the value up to one decimal place. It has to be between 0 and 1,000 points. If you like to use a calculator you can activate it by clicking on the symbol right to the input field. You end the period by pushing the OK-button, then you reach the next period.

On the screen you will be shown information about all past periods. This contains the optimal value of the period, the probability p , the information, if you were able to set a new value, the value set for this period, and the loss and earning in points.

The following figure shows you the input mask:

[Display as Figure A1]

Consider that the optimal value for the *current* period is always shown in blue.

Payoff

The following conversion rate will apply:

$$\begin{aligned} 1 \text{ point} &= 0.0001333 \text{ euros} \\ \text{or } 1 \text{ euro} &= 7,500 \text{ points.} \end{aligned}$$

In addition to your earnings you can reach in this experiment a **show-up fee** of 4 euros is paid.

End

After filling in a short questionnaire you will be called separately to the payoff. Please bring the card indicating your workstation number and the filled-in and signed receipt. The payoff will be anonymous and private.

To avoid that your name can be linked to your experimental data, you will receive an **additional** amount between 0 and 1 Euro. This amount will be calculated randomly and added to your experiment earning.

Comprehensive questions

The probability that you can reset the value in the next period is 50%.

What is the probability not to set a new value in the next two periods?

[Answer: $.5^2=.25$]

What is the probability not to set a new value in the next four periods?

[Answer: $.5^4=.0625$]

Assume that you had set a value of 100 and that you have not received a signal to reset your value for four periods.

Period	Optimal Value	Set Value	Loss	Earning
1	120	100	[Answer: $2.5(100-120)^2=1,000$]	[Answer: $1,000-1,000=0$]
2	80	100	[Answer: 1,000]	[Answer: 0]
3	150	100	[Answer: 6,250]	[Answer: 0]
4	100	100	[Answer: 0]	[Answer: 1,000]
	Total			[Answer: 1,000]

1. Please calculate the losses for all periods!

2. Please calculate the earnings of all periods and the total of them!

APPENDIX C

Table C1: Observations per treatment

	# Observations	# Observations	# Observations	# Observations	# Observations
	Price set	Price < lower bound	Price > upper bound	Period > 99	Valid observations
Benchmark	616	9	12	35	560
Treatment 1	2,632	9	6	181	2,436
Treatment 2	481	3	0	37	441
Treatment 3	430	0	0	23	407
Treatment 4	552	7	5	35	505
Treatment 5	1,156	2	0	72	1,082
Treatment 6	802	5	3	48	742