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by Alfonso Rosolia

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DOES INFORMATION ABOUT CURRENT INFLATION AFFECT EXPECTATIONS AND DECISIONS? ANOTHER LOOK AT ITALIAN FIRMS

by Alfonso Rosolia*

Abstract

I document the response of the inflation expectations, and pricing and labour demand decisions of Italian firms to randomly provided information about recent inflation and assess the causal effect of the former on firms' decisions. I use a standard menu cost model to show that conventional IV2SLS estimates based on variation of agents' inflation expectations generated by experimental manipulation of their information sets are likely devoid of casual content because in such experimental settings some assumptions required for their causal interpretation fail. I discuss alternative estimators based on assumptions more likely to be consistent with the underlying theoretical framework. Empirically, I find that randomly informed firms substantially revise their inflation expectations but do not revise pricing and hiring decisions. Causal inference from appropriate estimators consistently reveals that the lack of reduced form effects reflects absence of statistically significant effects of expected inflation on firms' decisions rather than offsetting responses. These results cast doubts on the possibility of obtaining substantial real effects through communication strategies that reach the general public more effectively.

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1 Introduction[*]

The toolkit of central banks has considerably expanded over the last decade. Monetary policy authorities have increasingly resorted to unconventional tools to pursue their statutory objectives among which steering agents' expectations, and inflation expectations in particular (Draghi (2019), Bernanke (2020), Lane (2020)). This choice is grounded on well-established evidence that central banks are able to shape the inflation expectations of professional forecasters and those derived from financial markets, who are generally seen as the first ring of the chain of transmission of monetary policy impulses[1]. More recently, the possibility that directly steering households' and firms' inflation expectations might generate additional policy space through the response of their interest-sensitive forward-looking decisions, and particularly so when policy rates are constrained by the effective lower bound, has also received attention (for example, Bernanke (2007), Blinder, Ehrmann, Fratzscher, De Haan and Jansen (2008), Coibion, Gorodnichenko, Kumar and Pedemonte (2020c)).

In this paper I specifically focus on firms and offer two main contributions. The first one is methodological. Empirical scrutiny of the expectational mechanism requires addressing the possibility that agents' inflation expectations are endogenously determined with respect to the outcomes of interest. Recent research increasingly relies on experimentally designed survey data collections that involve manipulation of the agents' information sets through the provision of specific pieces of information to randomly selected groups of survey subjects. Randomised control trials (RCT) are then used to study the response of agents' expectations to information, and thus assess their degree of awareness of the information underlying the signal (for example,

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[1]For example, Kuttner (2001), Cochrane and Piazzesi (2002), Bernanke and Kuttner (2005), Gürkaynak, Sack and Swanson (2005), Gürkaynak, Levin and Swanson (2010), Del Negro, Giannoni and Patterson (2015), Hanson and Stein (2015), Nakamura and Steinsson (2018), Hansen, McMahon and Tong (2019).

Cavallo, Cruces and Perez-Truglia (2017), Coibion, Gorodnichenko and Kumar (2018), Frache and Lluberas (2019), Bottone, Tagliabracci and Zevi (2021)), and as a source of exogenous variation of expectations to be exploited in conventional IV2SLS settings to document the causal mechanisms of interest (for example, Coibion, Gorodnichenko and Ropele (2020b), Coibion, Georgarakos, Gorodnichenko and Van Rooij (2019a), Coibion, Georgarakos, Gorodnichenko and Weber (2020a)).

I argue that the experimentally generated cross-sectional variation in firms' information sets, a key element to address the causal question of interest, is not in itself sufficient to support sound causal inference. Causal interpretation of empirical objects based on such exogenous variation requires complementary assumptions to hold; among these, the often overlooked ones on the relationship between the experimentally manipulated variable and the endogenous variable and between the endogenous variable and the outcomes of interest. To assess the plausibility of the assumptions required by commonly used empirical tools for causal analysis, I combine a simple learning model that describes how the experimental set up affects the endogenous variable of interest with a conventional menu cost model of price setting that illustrates the cross-sectional causal relationship between expected inflation and prices and labour demand[2]. I show that even in such a simple theoretical framework with very limited unobserved heterogeneity, conventional IV2SLS estimates essentially based on comparisons of conditional means of outcomes and endogenous variables across randomly determined groups of subjects are likely to be unsuited to support causal statements because the assumptions required to this end are inconsistent with the underlying structural relationships between instrument, endogenous variable and outcomes (Imbens and Angrist (1994)). I then discuss the relevant aspects of the experimental design and of the underlying behavioural models that must be addressed in order

[2]Menu cost models have been shown to be highly consistent with many features of the cross-sectional dispersion of prices across firms and with its evolution over time (see, among others, Nakamura and Steinsson (2008), Gagnon (2009), Midrigan (2011), Kehoe and Midrigan (2015), Alvarez, Beraja, Gonzalez-Rozada and Neumeyer (2018), Nakamura, Steinsson, Sun and Villar (2018), Karadi and Reiff (2019)), in contrast with the predictions of competing representations.

to maintain consistency between the theory and the interpretation of empirical objects and argue that causal interpretation of alternative, less conventional, estimators rests on assumptions more likely to be consistent with the underlying theoretical model.

The second contribution of the paper is empirical. I use the above theoretical results to assess whether firms' inflation expectations affect their pricing and labor demand decisions. I exploit the Survey of Inflation and Growth Expectations (SIGE) run quarterly by the Bank of Italy since the end of 1999. Quite uniquely, for over twenty years the survey has collected *quantitative* point information about firms' expected consumer price inflation at several horizons, and about past and expected future changes in own selling prices; the panel structure further allows observing future developments in labour demand. Importantly, since the third quarter of 2012, the survey also includes a randomised control trial (RCT) in which a random subset of two thirds of the firms is presented at the very beginning of the questionnaire with the most recent reading of consumer price inflation while the remaining third is not told anything[3].

Consistently with a large body of empirical evidence, I find that firms' average inflation expectations generally react in a statistically significant way to being provided external information. The response is generally not larger than half a percentage point in absolute value and its sign varies over time. These features, together with the observation that average expected inflation of both groups of firms moves closely in line with the inflation expectations of professional forecasters, suggest that Italian firms are more attentive to the broader macroeconomic outlook and more able to formulate expectations than their New Zealand and US counterparts (Coibion et al. (2018), Candia, Coibion and Gorodnichenko (2021)). Furthermore, the finding that exogenously provided publicly available information has varying effects on average expectations across waves of the survey suggests that the incentives of firms to actively seek information evolve over time (for example, Maćkowiak and Wiederholt (2009)), so that the exogenously provided public information is not necessarily missing from their information set and occasion-

[3]Since the beginning of the survey and until 2012:2 all firms were presented with this background information.

ally no difference is detected across the two groups' inflation expectations. On the contrary, I find no evidence that average own price changes and labor demand are different across the two groups of firms, even when the outcomes of interest are referred to subsequent periods so as to allow for the possibility of delayed effects of the information assignment. These findings broadly carry over to comparisons of the cross-sectional marginal distributions of the variables of interest across assignment status. Quarter-specific conditional quantile regressions show that the response of the quantiles of expected inflation are highly consistent with a learning model whereby subjects for whom the signal turns out to be above current expectations revise them upwards and viceversa. Once again, however, the corresponding comparisons of the cross-sectional marginal distributions of contemporaneous and subsequent own price changes and labour demand do not reveal any statistically significant difference. Overall, this reduced form evidence suggests that communication strategies aimed at reaching out firms more effectively with information about the macroeconomic outlook or economic policies, while inducing clearly detectable revisions in their inflation expectations, are unlikely to further achieve substantial aggregate effects on labor demand or price dynamics.

Yet, albeit suggestive, these findings are silent about whether firms act on their inflation expectations. For example, if the positive response of prices to expected inflation is heterogeneous across firms, it might happen that the price increases of firms that revise their inflation expectations upwards compensate the price decreases of firms that revise them downwards so that the average price change across exogenously determined assignment groups is negligible. To produce reliable causal inference additional assumptions must be invoked that allow linking the marginal distributions of inflation expectations to those of outcomes across exogenously determined assignment status (see, for example, Heckman, Smith and Clements (1997)). To this end, I explore alternative estimators transparently discussing the assumptions each of them requires for a causal interpretation and their consistency with the underlying economic theory. Across all methods and sets of assumptions, I am never able to detect any evidence of a statistically relevant causal effect of expected inflation on contemporaneous or future firms' own price changes and labour demand. Furthermore, irrespective of their statistical significance, quarter-specific point estimates are often implausibly large in absolute value and equally likely to be positive and negative with no clear pattern over time, thus not pointing towards a demand- vs supply-side view explanation of the behaviour of economic agents (Coibion et al. (2020c)). I conclude that it is highly unlikely that firms' decisions respond to revisions in their expected inflation, even when these revisions turn out to be large. Hence, it is doubtful that strategies specifically designed to steer firms' expectations have any real effect at all.

This paper contributes to a small set of studies that focus on firms' expectations[4]. Despite the fact that, as price setters, firms play a primary role in transmitting monetary policy impulses to the real economy by adapting their demand for inputs, prices, and supply empirical research on how their expectations form and affect their choices is still rather scant, mostly because surveys of firms' expectations are extremely rare and typically only collect qualitative information on the direction and possibly intensity of expected price changes. Among the few exceptions, Frache and Lluberas (2019) detect informational frictions among Uruguayan firms, that become milder when wages are renegotiated; studying the inflation expectations of Italian firms, Conflitti and Zizza (2020) also find that they are significantly shaped by wage renewals, Bartiloro, Bottone and Rosolia (2019) document that the their dispersion responds to macroeconomic conditions, decreasing when the output gap is lower and current inflation closer to the ECB target and Bottone and Rosolia (2019) show that they respond to monetary policy shocks identified from high frequency movements in the term structure of interest rates; Enders, Hünnekes and Müller

[4]Most existing research on the formation of expectations and their properties has focused on households, for which suitable data are more often available. For example, Carroll (2003), Mankiw, Reis and Wolfers (2003), Manski (2004), Coibion and Gorodnichenko (2015), Armantier, Nelson, Topa, van der Klaauw and Zafar (2016), Binder (2017), Cavallo et al. (2017), Manski (2017), Bachmann, Berg and Sims (2015). The main conclusions are that households form their inflation expectations on the basis of past experiences (Malmendier and Nagel (2015)), are largely unaware of broadly available public information (Binder (2017), Binder and Rodrigue (2019), Coibion, Gorodnichenko and Weber (2019b), Coibion et al. (2020a)), are often unable to recognize more reliable sources of information and tend to be less responsive to information the lower the underlying inflation rate (Cavallo et al. (2017)).

(2019) also find that the qualitative assessment of future price dynamics of German firms responds to shocks to short term interest rates; on the contrary, Coibion et al. (2018) and Candia et al. (2021) find that New Zealand and US firms are quite inattentive to inflation developments and broadly unaware of monetary policy.

To my knowledge, only Coibion et al. (2018) and Coibion et al. (2020b) specifically assess the expectational mechanism by exploiting direct information on firms' expectations and decisions within well defined experimental frameworks that allow addressing endogeneity and reverse causality concerns [5]. While mostly focusing on the formation of expectations, Coibion et al. (2018) also provide some causal evidence that New Zealand firms that revised sharply downwards their inflation expectations when randomly selected to be informed about the central bank inflation target also revise significantly downwards their investment expenditure and labour demand.

My paper is more closely related to Coibion et al. (2020b), which is based on the same experimental data and specifically "[...] study the causal effect of inflation expectations on firms' economic decisions. [...]". They reach opposite conclusions, however. Specifically, they find that "[...] higher inflation expectations on the part of firms lead them to raise their prices, increase demand for credit, and reduce their employment and capital. However, when policy rates are constrained by the effective lower bound, demand effects are stronger, leading firms to raise their prices more and no longer reduce their employment. [...]" and conclude, among other things, that "[...] communication policies of central banks may be able to directly affect firms' decisions through their inflation expectations, if these policies can reach firms. [...]". I show that this divergence stems from the fact that the empirical specification of their main IV regression implies that the IV estimates are essentially identified out of the correlation over

[5] Despite the greater availability of survey data, even for households only few studies address the issue of whether inflation expectations causally affect their decisions: Armantier, Bruine de Bruin, Topa, van der Klaauw and Zafar (2015) provide experimental evidence that individuals act on their inflation expectations in making financial decisions; Coibion et al. (2019a) find that higher expected inflation reduces and delays spending on durable goods (see Bachmann et al. (2015) for a different take).

time of current inflation with the expectations of both informed ad uninformed firms rather than out of the exogenous variation across the two groups generated by randomisation. As such, they are unlikely to support causal inference and cannot be compared with the findings of the present paper.

The paper is organized as follows. In Section (2) I briefly illustrate the survey and the experimental research design. In Section (3) I use a simple theoretical framework to discuss the implications for the choice of appropriate empirical tools for causal inference. The empirical evidence is presented in Section (4) and discussed in Section (5). I then conclude.

2 Data

The Bank of Italy's Survey of Inflation and Growth Expectations is a quarterly survey of firms with at least 50 employees operating in the manufacturing, construction and private services sectors (Banca d'Italia (1999-2020)). It started in the fourth quarter of 1999 and now focuses on a sample of about 1,200 firms. The survey has mainly a panel structure, with periodic refreshments to make up for panel attrition. It collects a host of quantitative and qualitative assessments of the broad macroeconomic outlook and of own firm conditions and decisions. Relevant to the present paper, the survey uniquely collects point values for the consumer price inflation expected by the firm at several future horizons, the change in own selling prices over the past 12 months, the expected change in own selling prices over the next 12 months and current employment. The panel structure allows observing, albeit only for panel firms, labour demand developments as well as other outcomes of interest in subsequent periods.

At the very beginning of the questionnaire and before any question is asked, firms are presented with the most recent reading of annual consumer price inflation in Italy and in the Euro area, which typically refers to two months earlier due to dissemination delays. Beginning in the third quarter of 2012, the provision of this piece of information is randomised: two thirds of the firms are still presented with recent inflation data while the remaining third is not. Since in 2017:2 the RCT has been expanded and now includes three information treatments: 3/5 of the firms receive information about recent inflation, 1/5 is presented with the ECB price stability goal and 1/5 is not presented with any piece of information[6]. Firms presented with the ECB target are dropped from the subsequent empirical analysis[7].

The assignment to the information treatment is persistent: firms assigned to either group in 2012:3, remained in the same group in subsequent waves of the survey; the same happened with the assignment to the three groups in 2017:2. New firms entering the sample after 2012:3 were randomly assigned to the relevant groups so as to preserve the size of the treatment groups; also in their case, the assignment is maintained in subsequent waves.

Figure (1) shows the average annual expected inflation one year ahead of firms presented with recent inflation data and of firms not presented with any information. The two time series track each other quite well and are remarkably in line with the currently available inflation rate (left panel) and with contemporaneous Consensus inflation forecasts over the same yearly horizon[8](right panel). The average expectations of uninformed firms appear to be slightly more stable than the corresponding expectations of informed firms, the Consensus forecasts and the currently available inflation rate; they are somewhat higher between 2012 and 2016, largely in line in 2017 and 2018 and again slightly above afterwards[9]. Differences are generally limited, however, and overall absent in periods of relative inflation stability. Specifically, the mean absolute difference between Consensus forecasts and expectations of uninformed firms

[6]Evidence that assignment to information groups is actually random and that panel attrition is unrelated to assignment status is reported in Appendix (A). See also Coibion et al. (2020b)'s online appendix.

[7]Bottone et al. (2021) specifically document the effects of this information treatment on firms' inflation expectations and conclude that, although firms are broadly aware of the ECB target, presenting firms with the specific wording of the target raise inflation expectations by 0.25 percentage points on average.

[8]Monthly Consensus forecasts are collected with reference to a fixed date (at the end of the current year, at the end of the next year). I follow Dovern, Fritsche and Slacalek (2012) and transform them into fixed-horizon forecasts (in the next 12 months) by weighting forecasts for the current and following year by the number of months each forecast contributes to the 12-months horizon.

[9]See Bartiloro, Bottone and Rosolia (2017) for a more extensive discussion of the consistency between the average inflation expected by firms and that obtained from professional forecasters.

is 0.3 percentage points and that with informed firms just over 0.2 points; median absolute differences are even lower (0.26 and 0.16 percentage points, respectively) and the largest ones are 0.86 and 0.72 percentage points. This suggests that Italian firms are on average largely aware of the overall outlook and able to formulate realistic expectations, broadly consistent with formulated by professional forecasters, in contrast to what is typically found in other surveys of firms. For example, Kumar, Afrouzi, Coibion and Gorodnichenko (2015) find that in 2013-14 the inflation expectations of New Zealand CEOs were on average over 3 percentage points higher than those of professional forecasters although realised inflation and the RBNZ expected inflation were relatively stable just below 2 percent; Candia, Coibion and Gorodnichenko (2020) find that in 2018-19, again a period of relatively stable inflation, US CEOs' average expected inflation is about 1 percentage point higher than those of professional forecasters[10].

3 A simple theoretical framework

In this section I describe the two theoretical underpinnings of the subsequent empirical analysis. On the one hand, I use a simple learning model to discuss the likely characteristics of the relationship between expected inflation and information assignment status generated by the RCT described above. On the other, I use a rather conventional menu cost model of price adjustments to discuss relevant features of the causal relationship between expected own price changes and expected inflation. I then discuss the implications of these theoretical features for the selection of adequate empirical tools to inform causal inference. In particular, I show that conventional IV2SLS estimates of the parameter of interest are unlikely to have a causal content and consider alternative approaches to causal inference based on assumptions that appear more consistent with the underlying theory and data.

[10]Households, too, tend to expect a much higher inflation than professional forecasters (Mankiw et al. (2003), Candia et al. (2020)).

3.1 How firms form expectations

The first piece of theory describes the empirical relationship between expected inflation and the provision of information about current inflation generated by the RCT. I begin by postulating a simple linear model that relates i's expected future inflation ($F_i\pi$) to its perceived current inflation (Π_i) and to other determinants that I assume are uncorrelated with its current perception (u_i):

$$F_i\pi = \gamma\Pi_i + u_i \tag{1}$$

This representation is general enough to accomodate several models of the formulation of expectations, from a simple adaptive mechanism based on the extrapolation of current inflation to more complex models that combine all the information available to i and potentially unobserved to the econometrician.

Consider a RCT consisting in presenting a signal π about current inflation to a randomly selected group of subjects ($I_i = 1$) and no information to the others ($I_i = 0$). As such, the experiment does not induce any direct random manipulation of the subjects' knowledge of current inflation Π_i; only the provision of information, I_i, is randomised. This additional information may however induce a revision of i's assessment of current inflation.

To understand how being presented with this information reflects on expected inflation, it is useful to recast the above in terms of potential outcomes. Specifically, let the pairs $\{\Pi_i^1, \Pi_i^0\}$ and $\{F_i^1\pi, F_i^0\pi\}$ be the perceived current inflation rate and the expected inflation of subject i, respectively, when and when not randomly selected to be presented with the signal.

It is plausible to assume that each firm assesses current inflation by combining all available information, so that $\Pi_i^1 = h(\pi, \Pi_i^0)$ where π is the experimentally assigned signal. Further assuming Bayesian learning and normally distributed prior and signal, as for example in Cavallo et al. (2017), leads to a parsimonious linear relationship between posterior and prior assessments and the signal

$$\Pi_i^1 = \omega\pi + (1-\omega)\Pi_i^0 \tag{2}$$

where ω measures the relative precision of the signal. Thus, firms revise their current assessment towards the randomly provided signal π whenever the signal is not aligned with their prior assessment. Importantly, the same value of the signal may be equally read as an inflationary or disinflationary shock and thus cause positive or negative revisions depending on i's prior assessment, Π_i^0.

Equations (1) and (2) imply that the revision of firms' inflation expectations induced by being presented with the signal follows a similar pattern. In fact,

$$F_i^0\pi = \gamma\Pi_i^0 + u_i \tag{3}$$

$$\begin{aligned} F_i^1\pi &= \gamma\Pi_i^1 + u_i \\ &= \gamma(\omega\pi + (1-\omega)\Pi_i^0) + u_i \qquad (4) \\ &= F_i^0\pi + \gamma\omega(\pi - \Pi_i^0) \qquad (5) \end{aligned}$$

Therefore, when firm i is exposed to the signal it revises its expected inflation by

$$F_i^1\pi - F_i^0\pi = \gamma\omega(\pi - \Pi_i^0) \tag{6}$$

whereby (under the reasonable assumption that $\gamma > 0$) firms that revised upwards their assessment of current inflation tend to revise upwards their inflation expectations and viceversa. Hence, a reasonable description of how firms update their expected inflation when information on current inflation is provided shows that being presented with a signal has heterogeneous effects on expected inflation whose signs depend on firms' prior assessment. Equation (6) also shows that the specific value of the signal presented to firms, π, carries no information on how expectations will be revised, even if only on average, unless one observes their prior assessment, Π_i^0.

3.2 How firms set prices

In this section use a benchmark menu cost model to characterize features of the relationship between expected inflation and expected change in own price over a given horizon that are relevant to the subsequent empirical analysis.

I specifically build on Nakamura and Steinsson (2008)'s partial equilibrium version of the model and their calibration, which I briefly summarize. Firms, indexed by i, produce using labour (L) with a linear technology $y_{it} = A_{it}L_{it}$ to satisfy the demand for their goods given by $d_{it} = D(\frac{p_{it}}{P_t})^{-\theta}$, where p_{it} is the nominal price charged by firm i in t and P_t is the aggregate price level in the same period. Under the additional simplifying assumption that the real wage is constant at $\frac{W_t}{P_t} = \frac{\theta-1}{\theta}$, Nakamura and Steinsson (2008) show that in equilibrium the firm's profit function can be written as

$$Y_{it} = D(\frac{p_{it}}{P_t})^{-\theta}(\frac{p_{it}}{P_t} - \frac{\theta-1}{A_{it}\theta}) - \frac{\theta-1}{\theta}KI(p_{it} \neq p_{it-1})$$

where $I(.)$ is an indicator function and K is the additional units of labour the firm must hire to adjust its nominal price. Firm's labour productivity evolves according to $\log A_{it} = \rho \log A_{it-1} + \epsilon_{it}$ with $\epsilon_{it} \sim N(0, \sigma_\epsilon^2)$; the aggregate price level evolves according to $\log P_t = \mu + \log P_{t-1} + u_t$ with $u_t \sim N(0, \sigma_u^2)$. Firms enter period t with the previous price, p_{it-1}, observe their idiosyncratic productivity, A_{it}, and the aggregate price level, P_t, and set their current price p_{it} to maximize the expected discounted flow of future expected profits.

Nakamura and Steinsson (2008) postulate that firms may revise prices every month and calibrate their model accordingly. I use their calibrated parameters and expand their set up in two ways. First, since I use the model to describe how firms' expected price revisions change with the underlying expected inflation rate I consider several different values of μ, the expected growth rate of the price level. Specifically, I solve the model for expected annual inflation rates between 1 and 5 percent with 0.5 percentage point increments, a range that includes their baseline value of roughly 2.5 percent. To preserve the relationship between the volatility of the price level and its trend implicit in their calibration, I define the variance of the shock to the (log) price level under alternative values of the average growth rate so as to keep the coefficient of variation constant at 1.5, the value roughly implied by their calibration[11]. Second, empirical evidence suggests a great deal of heterogeneity in the frequency with which firms perform price reviews. For example, the ECB surveys on price setting behaviour in the Euro area (Fabiani, Loupias, Martins and Sabbatini, eds (2007)) found that more than half of the firms reviews its prices at most three times a year and only one fourth once a month; actual price changes appeared to be even less frequent, 86 percent on firms performing at most three annually. To assess how this potential additional source of heterogeneity affects the relationship between own expected price changes over a given horizon and expected inflation, I also consider settings in which firms may revise prices less frequently than in Nakamura and Steinsson (2008), namely every two months, every quarter, every semester, and adjust the underlying stochastic processes accordingly[12].

I solve the firm dynamic problem by value function iteration. I use the policy function to compute the object of interest, $\Delta^n_s(\pi) = \frac{Ep_n(p_0/P_0, A_0)}{p_0}$, that is the cumulative price change a firm expects to record one year (n decision periods per year) ahead given the initial state $s = \{p_0/P_0, A_0\}$ and expected annual inflation π. The quantity $\beta^n_s(\pi) = (\Delta^n_s(\pi+\delta)) - \Delta^n_s(\pi))/\delta$ is thus the treatment effect of interest generated by a plausible representation of the firm's decision problem.

I compute β setting $\delta = 0.005$ and document its features focusing only on points of the state space with positive probability in (partial) equilibrium. Figure (2) displays the cross-sectional distribution of $\beta^n_s(\pi)$ at various levels of expected inflation (x-axis) and under alternative as-

[11]However, given the limited range of alternative values of trend inflation I consider, results do not change significantly if the variance of the shock is simply kept at its original value.

[12]The computational solutions of the dynamic problems are based on discrete approximations of the continuous stochastic processes obtained using Tauchen (1986). Let Q_m be the monthly transition matrix associated with the continuous stochastic process of interest (firm specific TFP and the aggregate (log) price level) under Nakamura and Steinsson (2008)'s calibration at monthly frequency. When I consider less frequent revision possibilities, say n times a year, I solve the dynamic problem using the cumulated transition matrix $Q_n = Q_m^{\frac{12}{n}}$.

sumptions about the annual frequency of price reviews. The response to a given change in expected inflation turns out to be quite heterogeneous across firms even when the the econometrician fails to observe only firms' current productivity and relative price. Even in Nakamura and Steinsson (2008)'s baseline calibration, in which prices are reviewed every month and expected annual inflation is 2.5 percent, half of the firms revise their expected price less than one for one against an increase in expected inflation. Heterogeneity is higher the less frequently prices are reviewed and the lower the expected inflation rate. In addition to being heterogeneous across firms, the effect of expected inflation on expected own price change is likely to be non linear. To show this, I summarize the firm-specifc heterogeneity of $\beta_s^n(\pi)$ across expected inflation rates with the ratio $cv_s^n = \sqrt{\sum_\pi (\beta_s^n(\pi) - \bar{\beta}_s^n)^2}/\bar{\beta}_s^n$ where $\bar{\beta}_s^n$ is the firm-specific average response, so that a linear response over the range $\pi \in [0.01, 0.05]$ would imply $cv_s^n = 0$. Table (1) summarizes the cross-sectional distribution of cv_s^n. Deviations from linearity are widespread and substantial, the more so the less frequently prices are reassessed.

To summarize, even a stylised menu cost model with only few sources of heterogeneity potentially unobserved to the econometrician gives rise to substantial heterogeneity in the response of own expected prices to a given change in expected inflation. This simple setup confines the presence of non-convex adjustment costs to prices. Yet, a large body of empirical evidence has documented that non-convex adjustment costs of capital and labour are also likely to be present (for example, Cooper and Haltiwanger (2006), Bachmann, Caballero and Engel (2013)). Therefore, in a more realistic model that extends the set of choice variables that are subject to non-convex adjustment costs the heterogeneity of responses against the same shock would naturally extend to other decision variables, and likely increase as a reflection of the greater and multidimensional underlying heterogeneity (Dixit (1997)).

4 Implications for the empirical analysis

The previous section has shown that the typical RCT involving the random provision of a signal implies that the response of expected inflation is heterogeneous in magnitude and sign and that even a very simple representation of the firm's pricing decision under minimal sources of unobserved heterogeneity implies that firms' responses to expected inflation are heterogeneous across firms. Causal inference on the relationship between outcomes of interest and inflation expectation must therefore be based on estimators whose causal interpretation rests on assumptions that are not inconsistent with those theoretical features.

Consider exploiting the random provision of the signal (I_i) as an instrument for expected inflation ($F_i\pi$) to estimate by IV

$$y_i = \kappa + bF_i\pi + \epsilon_i$$

Angrist and Imbens (1995)'s LATE theorem lays out the assumptions required to interpret cross-sectional IV estimates of b as the average causal effect (ACR) of expected inflation on outcome y. In particular, the theorem requires that either the treatment effect (i.e. the response of own expected prices to expected inflation) is constant and common across firms or that the instrument shifts, if at all, the treatment variable in the same direction for all units (monotonicity assumption). Because, based on the discussion in the previous section, the first assumption is unlikely to be consistent with a standard menu cost model and the second one is unlikely to be consistent with a conventional learning model a causal interpretation of conventional IV2SLS estimates is therefore not warranted in principle. To gather an intuition of why this is the case, assume that the structural relationship of interest is linear but heterogeneous across units[13], $y_i = \beta_i F_i\pi + u_i$, and consider the Wald estimator $\hat{b} = \frac{E(y_i|I_i=1)-E(y_i|I_i=0)}{E(F_i\pi|I_i=1)-E(F_i\pi|I_i=0)}$ (Angrist, Graddy and Imbens (2000)). Using expressions (3) and (5) with the structural relationship and

[13] Note this, too, is a rather restrictive assumption in light of the features of the menu cost model, which implies a non-linear relationship between price changes and expected inflation.

the fact that $E(F_i\pi|I_i = s) = E(F_i^s\pi)$, the expression for $\hat{b}$ can be rewritten as:

$$\hat{b} = \frac{E(\beta_i(\pi - \Pi_i^0))}{E(\pi - \Pi_i^0)}$$

which shows that the Wald estimator can be interpreted as a weighted average of the individual effects β_i with weights proportional to the revision in expectations induced by the signal provided $(\pi - \Pi_i^0)/E(\pi - \Pi_i^0) \geq 0 \quad \forall i$ that is, all units revise their expectations in the same direction. Hence, conventional IV2SLS estimates occasionally retain the possibility of a causal interpretation only provided the data are not clearly at odds at least with the monotonicity assumption. Fortunately enough, this can be verified by checking the necessary condition that the CDFs of the endogenous variables across assignment status do not cross, which I defer to the next section[14].

To overcome the potential limitations of conventional IV2SLS as a source of causal inference on the effects of expected inflation of firms' decisions in the present empirical setting, I complement standard IV2SLS estimates of the effects of interest with estimates obtained under two alternative sets of assumptions for casual inference.

First, I estimate a set of IV quantile regressions (IVQR); Chernozhukov and Hansen (2005) establish the conditions under which the IVQR estimand identifies the population quantile treatment effects, that is the causal effect of the treatment variable at specific quantiles of the distribution of the outcome variable. Relevant to the present context, monotonicity of the effect of the instrument on the treatment variable is not required. Rather, a causal interpretation of

[14]This brief discussion of the potential pitfalls of IV estimates of the effects of expected inflation on firms' outcomes has focused on cross-sectional estimates based on comparisons across assignment status. It could be argued that, for all practical purposes, the variation over time of the signal offers an additional source of identification because over time firms are exposed to different signals, against which one can assess their responses. However, this approach leads to an even more fundamental mistake. Intuitively, to be a valid source of causal inference the time variation of the signal should not affect the expectations of uninformed firms; only informed firms should be exposed to it. In practical terms, this amounts to assuming an extreme form of firms' inattention whereby their assessment of current inflation is unrelated to actual inflation. The assumption is clearly at odds with the time series evidence of section (2) that shows that the expectations of uninformed firms move closely with current inflation, with the expectations of professional forecasters and with those of informed firms. I provide a formal proof of this argument in Appendix (F).

IVQR estimates rests on the assumption of rank similarity, that is a restriction on the evolution of individual ranks across treatment values[15]. In the present context, IVQR rank similarity requires that if firm a expects a lower price change than firm b for a certain (common) expected inflation rate, it does systematically so for any expected inflation rate and that perturbations of the counterfactual rankings are unsystematic; under the stricter rank invariance assumption, that excludes the possibility of unsystematic slippages from the ranking, even the distribution of individual treatment effects is identified. Unfortunately, the rank similarity assumption can be tested only in specific cases which do not include the present one[16]. Yet, the pricing behaviour implied by menu costs models is largely consistent with this assumption. Indeed, in the several simulations of the menu cost model discussed above rankings are always preserved across the different values of underlying expected inflation.

Second, I exploit the structure imposed by the learning model on the relationship between the instrument and the treatment variable to make transparent assumptions that restore the validity of the LATE theorem in specific subsamples of the data. Specifically, I follow Cavallo et al. (2017) and assume that all heterogeneity in expected inflation is the reflection of heterogeneity in the assessment of current inflation, rewriting equation (1) as

$$F_i\pi = \mu + \gamma\Pi_i \tag{7}$$

[15] Alternatively, Abadie, Angrist and Imbens (2002)'s local quantile effect model identifies the causal effect of treatments on quantiles of the distribution of the outcome among the treated subpopulation; yet, it still requires a monotonicity assumption that restricts the relationship between the instrument and the treatment. Chernozhukov and Hansen (2005)'s rank similarity assumption imposes instead some restriction on the heterogeneity of treatment effects (Heckman and Vytlacil (2007)). See Melly and Wüthrich (2017) and Wüthrich (2020) for a discussion of the two approaches and underlying assumptions.

[16] To the best of my knowledge, the possibility of testing the rank similarity assumption is extremely limited. Kim and Park (2017) show that rank similarity is fundamentally untestable within the empirical model that is, additional information is required. For the binary treatment case, Frandsen and Lefgren (2018) provide a formal test when, in addition to selected covariates, an auxiliary predetermined variable is available that predicts outcome but is uncorrelated with the instrument; Wüthrich (2019) shows a test is possible if the model is overidentified. No results are available for the multivalued and continuous treatment cases. Rank invariance is generally untestable too. I thank, without implying, Kaspar Wüthrich for clarifying several methodological details.

It is easy to show that this assumption and the learning mechanism in equation (2) imply that

$$F_i^0\pi > F_j^0\pi \iff F_i^1\pi > F_j^1\pi \quad \forall \{i,j\} \tag{8}$$

that is the ordering of firms according to the value of the treatment, their expected inflation, is preserved across assignment status. Therefore, letting $\{G_0, G_1\}$ be the empirical cross-sectional distributions of expected inflation conditional on randomly determined assignment status, pairs $\{q_0^\tau, q_1^\tau\}$ such that $G_0(q_0^\tau) = G_1(q_1^\tau) = \tau$ are the sample analogs of the counterfactual expected inflation rates $\{F_i^0\pi, F_i^1\pi\}$ of firm with rank τ[17]. This has two implications. On the one hand, comparisons of corresponding quantiles across the distributions of expected inflation conditional on assignment status allow inferring the distribution of individual revisions caused by information provision, $(F_i^1\pi - F_i^0\pi)$. On the other, comparisons of other outcomes of firms at the same relative position in the distributions of expected inflation conditional on assignment status offer an estimate of the effect of expected inflation on those outcomes. More generally, from equation (8) it also follows that if τ is such that $q_0^\tau < q_1^\tau$ then $F_i^0\pi < F_i^1\pi$ for all firms with rank lower than τ (and if τ such that $q_0^\tau > q_1^\tau$ then $F_i^0\pi > F_i^1\pi$ for all firms with rank higher than τ). Therefore, under assumption (7) monotonicity of the treatment effect is restored over specific segments of the conditional cross-sectional distributions of expected inflation, allowing for a causal interpretation of IV2SLS conducted over these subsamples.

[17] Note the resemblance with the rank invariance assumed by Chernozhukov and Hansen (2005). In their set up, however, rank invariance refers to the outcomes of interest across endogenous treatment levels; in the present setting it refers to the treatment variable across exogenous assignment status and is the natural consequence of a structural description of the learning and forecasting processes. In Chernozhukov and Hansen (2005), because of the endogeneity of the treatment variable, corresponding empirical quantiles of the outcome distribution across treatment values hardly represent pairs of counterfactual outcomes; in the current setup, because of the exogeneity of assignment status (and under the assumptions of the theoretical model), corresponding empirical quantiles τ of the conditional distributions of expected inflation are an estimate of the pair $\{F_i^0\pi, F_i^1\pi\}$ for firm with rank τ.

5 Empirical evidence

In this section I pursue the intuitions discussed above using the Bank of Italy's Survey on Inflation and Growth Expectations. I exploit the availability of many survey waves covering the period 2012:3 and 2019:4, to estimate quarter-specific models so as to account for the possibility that the relationships of interest evolve over time. I start with a description of how firms respond to being exposed to potentially new information about inflation. Comparisons of moments of the empirical cross-sectional conditional distributions of the variables of interest across assignment groups shed light on the extent of informational frictions, whereby firms are not aware of recent macroeconomic developments and adjust their decisions upon being informed, and on the aggregate effects of mitigating these frictions. I then turn to studying the causal effect of expected inflation on firms' decisions. To this end, I present results obtained with different estimators, each requiring different assumptions for a causal interpretation.

5.1 The effects of exposure to information

To assess how providing potentially unknown information shapes average firms' expectations and decisions I estimate, separately for each quarter t between 2012:3 and 2019:4, linear regressions

$$y_{it+k} = a_t + b_t I_{it} + d_t X_{it} + e_{it} \tag{9}$$

where y_{it+k} is the outcome of interest, possibly measured k periods ahead, $I_{it} = 1$ if firm i has been randomly selected to receive information about current inflation at survey t and $I_{it} = 0$ otherwise and X_{it} is a set of controls including the change of own selling price over the previous year, and dummies for firm size, industry and area. I use Huber-White robust standard errors[18].

Figure (3) reports estimates of b_t for annual expected inflation ($y_{it} \equiv F_{it}\pi$) one- and two-

[18] All results in the paper are based on unweighted regressions. Results of weighted linear regressions as well as of linear regressions based on untrimmed samples are reported in tables (B.1)-(B.12) of Appendix (B).

year ahead and for the average expected inflation rate between 3 and 5 years ahead collected at time t along with 95-percent confidence intervals based on Huber-White robust standard errors. Several things stand out. First, point estimates of the effect of being presented with recent inflation data on average expected inflation are very precise and generally statistically different from zero, consistently with the existing evidence that the general public often revise their expectations even when shown publicly and easily available information (for example, Cavallo et al. (2017), Coibion et al. (2018)); consistently with equation (8), the few instances in which estimated coefficients cannot be rejected to be zero with at least 5 percent probability correspond to point estimates that are actually closest to zero, suggesting that in those quarters the information presented to firms was on average already embedded in the firms' prior assessment of current inflation ($\pi_t - E(\Pi^0_{it}) \simeq 0$). Second, in any quarter the change in average expected annual inflation is very much the same across forecast horizons, suggesting that exposure to recent annual inflation data affects the fundamental assessment of inflation pressures rather than their time profile. Third, the effects are overall limited, at most around half a percentage point, but vary over time, both in magnitude and in sign; they are at best only weakly related to the inflation rate presented to firms, consistently with the fact that the value of the signal carries in itself no information content. For example, between 2013:2 and 2015:4 inflation figures shown to firms went from 1.3 to as low as -0.5 percent while the mean gap in expectations hoovered steadily around minus half a percentage point[19].

In figures (4) to (6) I report the estimated effects of exposure to information collected at time of interview on other forward-looking outcomes of interest. Figure (4) focuses on firms' assessments at time t of the overall macroeconomic outlook and of their own specific business

[19]Bartiloro et al. (2019) use the same survey to document a statistically significant difference between the variances of the sample distributions of expected inflation conditional on information assignment. They show that under some assumptions the variance gap can be interpreted as a measure of the informativeness of the signal and document it is strongly correlated with descriptors of the business cycle. More generally, Cavallo et al. (2017) compare the responses to information provision of US and Argentinian consumers' average inflation expectations and conclude that consumers assign a lower weight to their prior assessment in low inflation environments.

perspectives over the next quarter[20]. Exposure to information has no detectable effects on the average assessments of the macroeconomic or own business outlook over the next three months. Estimates are quite imprecise and point estimates are often close to zero. These two variables are appealing as they are likely to capture, albeit indirectly, the effects of exposure to inflation information on the expectations about real activity in the very short run. Yet, any potential effect that is not large enough might go undetected given the coarseness with which they are collected.

Therefore, in figures (5) and (6) I focus on developments in own prices and labor demand and exploit the panel dimension to recover actual developments in own prices and labor demand in subsequent quarters ($k > 0$), so as to address the possibility that firms take time to adjust to the new information set as, for example, suggested in Coibion et al. (2020b). Specifically, I estimate equation (9) using as dependent variables, respectively, the expected change in own price over the next year reported at the time of the interview, and the change in own price over the past 12 months observed 1, 2 and 4 quarters after exposure (figure 5), and (log) employment observed 1, 2, 3, and 4 quarters after exposure to inflation data (figure 6). The figures report, as before, the point estimates of the effects of assignment status and the associated 95 percent confidence intervals based on Huber-White robust standard errors[21]

[20]Specifically, firms are asked to report the probability they assign to an improvement in the macroeconomic outlook over the next quarter and qualitatively assess how their business will evolve. The former variable is collected in 6 bins (0, 1-25, 26-50, 51-75, 76-99, 100) which I code in the dependent variable by assigning the mid-point of the interval or the specific point value; the latter variable is collected as worse (-1), stable (0), better (+1), which I directly use as dependent variable.

[21]Note that persistence of the random assignment implies that $I_{it} = I_i \quad \forall t$ in which i participates in the survey. Absent changes in the sample due to attrition and refreshments, even with random assignment of I_i estimates of b from $y_{it+k+1} = \alpha + bI_{it} + \theta X_{it} + e_{it}$ and $y_{it+k+1} = \alpha + bI_{it+k} + \theta X_{it+k} + e_{it+k}$ might differ because the control set includes variables that are potentially affected by exposure (e.g. firm size or past own price changes). More in general, this represents a potential "bad control" problem (Angrist and Pischke (2009)) whereby estimates of the causal parameter of interest are biased if a control variable is itself affected by the randomly assigned exposure dummy. To address this concern, I have tested that coefficient estimates are unaffected by the exclusion from the control set of past price changes and firm size dummies, the two most likely endogenous variables. Results reported in Appendix (C) show that the null hypothesis that estimates of the effect of exposure with and without these controls are equal can basically never be rejected at conventional levels of significance.

In sharp contrast with the findings for expected inflation, exposure to recent inflation data appears to have no detectable effect on the average size of currently expected or subsequently recorded own price changes or on (log) labor demand in the following quarters. Estimated differences can almost never be rejected to differ from zero at conventional levels of statistical significance[22].

This evidence sheds light on the effects of exposure to information on *average* expectations and outcomes. However, theory suggests the individual effects of interest could be heterogeneous in size and sign, depending on the prior assessment of current inflation. Hence, focusing on average effects may be misleading as individual responses of opposite signs cancel out.

Further insights can thus be drawn from comparisons of moments of the marginal distributions of the variables of interest across assignment status other than the mean. For example, a more detailed description of the effects of exposure on marginal distributions allows dealing with the possibility that statistically significant heterogeneous effects cancel out in the aggregate[23]. Operationally, for each quarter I estimate quantile regressions for the 20 vingtiles (5th, 10th,..., 90th, 95th) of each dependent variable conditioning, as above, on the assignment dummy, I_{it}, past price change and a set of dummies for firm size, geographical area and sector of activity. This exercise generates an enormous amount of estimates: for a given dependent variable there are between 500 and 600 coefficients, depending on whether the dependent variable is observed at the time of the assignment (expected inflation and own price change) or at subsequent waves (labor demand and future price changes).

Figure (7) offers a first summary of the statistical significance of these estimates. Each panel of the figure focuses on a specific dependent variable (expected inflation at all horizons, expected and future observed price changes, future labor demand) and reports the distribution

[22]Point estimates and associated robust standard errors are reported in tables (B.1)-(B.12) of Appendix (B).

[23]Comparisons of marginal distributions across assignment status are obviously not sufficient to draw inference on the distribution of individual effects unless additional assumptions are made. This is the goal of the next section.

of the t-statistics of the estimated effect of information exposure across the 20 quantiles and survey waves[24]; vertical bars represent the ± 1.96 value for 5 percent statistical significance. To display the distribution of these t-statistics on a common support I have top- and bottom-coded the t-statistics for expected inflation, reported in the panels of the first row, at ± 3.5. The figure shows that exposure to inflation data has clearly detectable effects on the marginal distributions of expected inflation at all horizons: most estimates have t-statistics well above conventional thresholds for statistical significance. Across all horizons, the median absolute t-statistic is 5.3 and the 25th and 75th percentiles are 2.7 and 8.3. Besides, the figure shows that positive and negative statistically significant effects are almost equally likely, consistently with the theoretical possibility of both downward and upward revisions against the same signal. On the contrary, hardly any effect is detectable on the marginal distributions of own expected and future realised price changes and of future labor demand: out of more than 2,000 coefficient estimates, in the case of own price changes only 13 have an absolute t-statistic larger than 1.96, the largest one being 2.6, while in the case of future labour demand the largest one is 1.8.

Figures (8) to (11) look more closely at how exposure to inflation data affects the marginal distribution of expected inflation at various horizons. Each panel reports the 95 percent confidence intervals of the effects of exposure on the 20 quantiles in a given quarter; as a reference, the figures also display a vertical bar representing the percentile of the marginal distribution of the expected inflation of firms not presented with information that corresponds to the inflation rate presented to informed firms in each quarter.

The patterns depicted in the figures are consistent with the implications of equation (6), whereby expected inflation increases upon being presented with the signal when the latter is above prior expectations and viceversa, so that negative and positive revisions may occur in the same period and against the same signal. This empirical feature is also broadly in line with

[24] Clearly, these t-statistics are not to be thought of as drawn from the same underlying distribution, as the parameters being estimated - the effect of exposure on a specific dependent variable - are most likely different across quantiles and over time.

available evidence in other settings that also documents significant revisions towards the signal in reaction to the provision of even widely available public information (Coibion et al. (2018) among New Zealand firms, Armantier et al. (2016) and Binder and Rodrigue (2019) among US consumers, Coibion et al. (2019a) among Dutch households, Cavallo et al. (2017) among US and Argentinian consumers; Frache and Lluberas (2019) among Uruguayan firms).

Importantly, this reduced form evidence also shows that in a learning setting the monotonicity assumption required for a causal interpretation of conventional IV2SLS estimates based on the random provision of information may be inappropriate. In the case of multivalued treatments a necessary condition for the monotonicity assumption to be satisfied is that the cumulative distribution function (CDF) of the treatment variable $F\pi$ conditional on being presented with the signal, $I = 1$, and the CDF of $F\pi$ conditional on not being presented with it, $I = 0$, should not cross[25]. Figures (8) to (11) show that this necessary condition is often not satisfied. This is particularly evident in the early quarters of the RCT and in general whenever the inflation rate presented to informed firms falls in the middle of the distribution of expected inflation of firms not given any information, so that upward and downward revisions coexist[26].

To sum up, the reduced form evidence presented so far shows that exposing firms to recent inflation data often has clearly detectable effects on their average inflation expectations at close and farther horizons. Sign and size of these effects vary over time, consistently with the evolution of the firms' underlying information set. The changes in average expectations result from changes in the marginal distributions of expected inflation that are broadly consistent with standard learning mechanisms, whereby upon receiving a signal agents revise their assessment towards the signal. Against these findings, there is no evidence that exposure to inflation data systematically affects future changes in own prices and labour demand, either on average or

[25]de Chaisemartin (2017) explores the conditions under which a causal interpretation of IV2SLS estimates of β is still possible even without monotonicity. The conditions he lays out, however, still include that the two conditional CDFs are ranked in a first order stochastic dominance sense and thus do not cross.

[26]More formal statistical evidence in this sense along the lines of Angrist and Imbens (1995) is presented in Appendix (D).

along the cross-sectional distribution.

These findings suggest that, in line with evidence available for households and firms in other countries, information frictions are widespread and many firms often do not fully employ the available information in forming their expectations. The degree to which this fails to happen seems to vary over time, thus suggesting a behavioural choice on the side of firms rather than the presence of exogenous external constraints[27]. However, the evidence also suggests that these information frictions have no detectable aggregate effects. The average pricing and hiring decisions of the group of firms exposed to inflation data are the same as those of the group of firms who have not received the information, even in periods when their average inflation expectations come to differ significantly. As a consequence, policies based on reaching firms more effectively with information about inflation are unlikely to have first order effects on aggregate pricing decisions and labour demand, irrespective of the specific underlying causal mechanisms.

The results are silent about the presence of a causal effect of expected inflation on firms' decisions, however. The lack of effects on average pricing decisions and labour demand against sizable effects on average expected inflation might equally be a consequence of the lack of causal effects of expected inflation, so that individual firms do not adjust their prices and labour demand when their inflation expectations exogenously change, or, for example, of heterogeneous causal effects that cancel out in the aggregate because of the heterogeneous revisions in expected inflation induced by the specific experimental setting. In the first case, policies based on steering individual expectations are outright ineffective; in the second case, their effects will crucially depend on the distribution of the individual responses to expected inflation and on the distribution of the revisions to inflation expectations induced by the specific policy.

[27]Evidence in this sense is presented, for example, in Cavallo et al. (2017) and Coibion et al. (2018). Bartiloro et al. (2019) specifically analyze the relationship between the size of the revisions in inflation expectations caused by the information assignment and the broader macroeconomic context and find evidence consistent with rational inattention on the side of firms.

Drawing reliable inference on the causal effects of interest requires invoking additional assumptions on the relationships between outcome, treatment and instrument. The next section tackles this issue and explores the inference obtained under three alternative and complementary sets of assumptions.

5.2 The effect of expected inflation

To address the question whether expected inflation has a causal effect on firms' decisions I present evidence based on alternative estimators, each interpretable in a causal sense under specific assumptions. I start presenting the results of conventional IV2SLS estimators and discuss their limitations in the present context. I then show results for Chernozhukov and Hansen (2005)'s IVQR estimator and conclude presenting results based on local estimates motivated by specific assumptions about the relationship between the treatment variable and the instrument. In all estimates, the endogenous variable is expected inflation one-year ahead.

5.2.1 IV linear regression

For each quarter t, I estimate separate IV linear regressions

$$y_{it+k} = \alpha_t + \beta_t F_{it}\pi + \theta_t X_{it} + e_{it} \tag{10}$$

where y_{it+k} is the dependent variable of interest, future own price changes and labor demand, $F_{it}\pi$ is i's expected annual inflation one year ahead, and X_{it} includes own price change over the previous year, and a set of dummies for firm size, geographical area and sector of activity. I use the randomly determined exposure to inflation data, $I_{it} \in \{0,1\}$ as instrument for expected inflation and make the (non testable) assumption that assignment status affects outcomes only through inflation expectations[28].

[28] Notice I do not exploit the variation over time stemming from the inflation rate presented to firms. As discussed above, it is not an exogenous source of variation as it is likely correlated with firms average prior assessments of current inflation. I discuss this point more at length in section (6).

As already discussed above, given the potential heterogeneity of treatment effects generated by conventional models of price setting these IV estimates have a causal interpretation under the assumption that the instrument, exposure to recent inflation data, has a monotonic effect on the treatment variable, expected inflation. However, as shown in the previous section, given a plausible mechanism guiding how agents assimilate new information, this assumption is likely to fail. Indeed, the reduced form evidence displayed in figures (8) to (11) shows that a necessary condition for this assumption to be satisfied, that the CDFs of the treatment variable conditional on assignment status do not cross, is often actually rejected by the data.

With these important caveats on the causal interpretation of IV results in mind, tables (2) and (3) report point estimates and Huber-White robust standard errors for the coefficient of interest, β, obtained for own price changes and for labour demand[29]. Against generally very strong first stage effects, the estimated coefficients on expected inflation reach conventional levels of statistical significance only in very few cases as concerns the response of own prices and even less so as concerns labor demand.

5.2.2 IV quantile regressions

Chernozhukov and Hansen (2005)'s IVQR model allows to recover the population distribution of the causal effects of expected inflation on own future prices and labor demand under the assumption of rank invariance across treatment values and, under a weaker rank similarity assumption, the population quantile treatment effects. These assumptions require that the ordering of firms' outcomes is preserved across values of expected inflation (invariance) or that individual ranks are subject only to unsystematic deviations across treatment values (similarity). In other words, if firm a changes its price less that firm b for a certain level of expected inflation, either it will do so at all levels of expected inflation or rank slippages are unsystematic.

[29]The coefficient estimates and robust standard errors of the corresponding first stage regressions are reported in tables (B.1) to (B.12) in the Appendix.

While the assumption is basically untestable, it is not in contrast with the simulation-based evidence from the stylised menu cost model of section (3.2) that accounts for major sources of unobserved heterogeneity in price determination[30].

I postulate a linear specification for the 1st to 9th deciles of the dependent variables and estimate it for each quarter using as control variables own past price change, and dummies for firm size, area and sector; the endogenous explanatory variable, expected inflation one year ahead, is instrumented with I_{it}, the assignment dummy[31].

An overview of the statistical significance of the many estimates is presented in figure (12). Each panel corresponds to a dependent variable and displays the distribution of the t-statistics of the effect of expected inflation one year ahead over time and deciles; vertical bars correspond to ± 1.96. Once again, conventional levels of statistical significance are detected only occasionally: out of about 1,000 coefficient estimates, for own price changes only 28 can be rejected to be zero with 5 percent significance and only 9 with 1 percent significance and for labour demand only 13 and 4, respectively. For both outcomes, half of the statistically significant effects are negative and half are positive, some of them also implausibly strong; also coefficients that do not reach conventional thresholds of statistical significance are roughly equally split between negative and positive values. Furthermore, tables (E.1) and (E.2) in the Appendix document that the few statistically significant estimates are not traceable to specific quarters or deciles.

5.2.3 Local IV2SLS

The last exercise exploits the fact that the learning mechanism together with a specific assumption on the determinants of cross-sectional heterogeneity of expected inflation imply that

[30] Heckman and Vytlacil (2007) argue that the rank similarity assumption is quite restrictive because it implies that subjects cannot choose the treatment taking into account the outcome it leads to. The objection is less relevant in the present context since firms do not select their expected inflation, the treatment value, comparing outcomes (prices, labour demand or profits) as instead would be the case in, say, the choice of a college major or of a training program as typically studied in the programme evaluation literature.

[31] I estimate the model with Kaplan and Sun (2017)'s smoothed IVQR estimator, using Kaplan (2020)'s sivqr Stata-package, setting 500 bootstrap replications and using the plug-in smoothing bandwidth.

ranks along the cross-sectional distribution of expected inflation conditional on assignment status are preserved across assignment status. In turn, this restores monotonicity of the effect of the instrument on the treatment on corresponding subsets of the support of the conditional distributions of expected inflation and thus a causal interpretation of IV2SLS obtained on these specific subsamples (section (4)).

To implement this intuition I partition the support of the empirical cross-sectional distributions of expected inflation conditional on assignment status into five bins each containing 20 percent of the observations. The cutoff points conditional on observable characteristics, $q_t^\tau(X, I)$, are estimated by conditional quantile regressions of expected inflation, so that $G(q_t^\tau(X, I)|X, I) = \tau$ where $\tau \in \{0.2, 0.4, 0.6, 0.8\}$, $I \in \{0, 1\}$. I assume that the conditional quantiles are linear in observable characteristics X that, as above, include past price change, and dummies for size, area ad sector of activity; quantile regressions are estimated separately for informed and uninformed firms and for each wave t. Each observation i with $\{y_{it}, F_{it}\pi, I_{it}, X_{it}\}$ falls in one of the five bins depending on the corresponding estimated conditional quantiles of expected inflation, $\{q_t^\tau(X_{it}, I_{it})|\tau = 0.2, 0.4, 0.6, 0.8\}$.

I then estimate IV regressions of equation (10) as above separately for each subsample. Figure (13) summarizes the statistical significance of the results. For each dependent variable, I display the pairs of IV (y-axis) and first stage (x-axis) estimates obtained on each subsample; the vertical and horizontal dark lines correspond to ± 1.96. Consistently with the evidence reported above, first stage effects are generally strong and statistically significant; on the contrary, IV estimates generally fail to reach conventional thresholds of statistical significance for any dependent variable under consideration even against sizable (and monotonic) responses of expected inflation to assignment status. Moreover, IV estimates again are equally likely to be positive and negative without a specific pattern over time, across dependent variables or along the fifths of the distribution of expected inflation.

6 Discussion of the results and conclusions

The evidence of the previous section shows that presenting firms with information on recent inflation has often statistically significant effects on their expected inflation. Consistently with the intuition that agents' information sets evolve over time, possibly reflecting the changing incentives to collect information, the sign and average size of these effects changes over time, occasionally being nil. Overall, the empirical pattern is largely consistent with standard learning models, in line with previous results on households and firms.

Against this evidence, current and future price changes and labour demand do not respond at all either to assignment status or to expected inflation. Given the credibility of the RCT, the reduced form results do not require specific assumption to be interpreted in a causal sense. While silent on causal mechanisms, they are suggestive that policies based on reaching the public more effectively with communication about the macroeconomic outlook may end up having little aggregate real effects even if average inflation expectations are significantly affected.

A causal interpretation of estimates of the relationship between prices or labour demand and expected inflation requires instead specific assumptions. I have shown that conventional models of price setting and learning may lead to inconsistencies between the structural relationships of interest and the assumptions required for the causal interpretation of empirical objects. To deal with this possibility, I have presented three sets of results, each based on different assumptions: conventional IV2SLS estimates, that constrain the relationship between the instrument and the treatment variable (monotonicity or common effect) while leaving the relationship between the outcome of interest and the treatment unconstrained; IVQR estimates, that constrain the relationship between the outcome and the treatment (rank similarity or invariance) while leaving that between the treatment and the instrument largely unconstrained; local estimates, that restore locally the conditions for causal inference required by conventional IV2SLS by assuming a specific structure for the formation of expectations.

These alternative approaches yield the same results. Firms do not appear to respond to expected inflation either contemporaneously or over longer horizons and responses fail to be significant even when the underlying revision of expectations is sizable. Across methods, the very few estimates that barely reach conventional thresholds of statistical significance are equally likely to be positive and negative. Irrespective of the specific statistical significance, the fundamental lack of a detectable pattern over time and across the cross-sectional distributions of the outcomes of interest also prevents a broader reading of the results. For example, it is unlikely that the effect builds up over time as a reflection of hysteresis since there is no evidence that later outcomes attract statistically significant coefficients more frequently. Similarly, point estimates being roughly symmetrically distributed around zero prevents conclusions about whether firms have a supply- or demand-side view of inflation as occasionally suggested to reconcile contrasting evidence (for example, Candia et al. (2020)). The results also reject the possibility that firms' responses to inflationary shocks may change when monetary policy is constrained by the effective lower bound to policy rates (for example, Coibion et al. (2020b)): estimates are not different or more likely to be statistically significant or positive rather than negative before and during the ELB period.

This fundamental lack of causal evidence in favour of a significant response of firm decisions to expected inflation stands in stark contrast with the available, albeit scant, evidence. To the best of my knowledge, the only two papers that have addressed the issue of the causal effects of expected inflation on firms' decisions in an experimental framework are Coibion et al. (2018), on New Zealand firms, and Coibion et al. (2020b), on Italian firms and based on the same data underlying the present paper. Coibion et al. (2018) are essentially concerned with how firms form their beliefs and expectations and address this specific issue in an experimentally designed ad hoc setting, which allows them to provide some descriptive evidence that when firms raise their inflation expectations they tend to mostly raise their employment and investment and to make little changes in their prices. On the other hand, Coibion et al. (2020b) are primarily concerned with the effects of expected inflation on firms' decisions focusing on prices and labour demand as well as on other outcomes. Their results are "[...] that higher inflation expectations on the part of firms leads them to raise their prices, increase demand for credit, and reduce their employment and capital. However, when policy rates are constrained by the effective lower bound, demand effects are stronger, leading firms to raise their prices more and no longer reduce their employment. [...]" Therefore, Italian firms appear to have more of a supply-side view of inflation with respect to New Zealand ones, although somewhat mitigated when monetary policy is constrained by the effective lower bound (Candia et al. (2020)).

Compared with those of the present paper, their results suggest a significantly broader scope for communication and information strategies that generate real effects through the management of firms' expectations (Coibion et al. (2020c)). While using the same data and RCT, their empirical strategy is different from that of the present paper. Specifically, they define a time-varying information treatment $T_{it} = I_{it} * \pi_t^*$ where π_t^* is the inflation data presented to firms surveyed at t and I_{it} is, as above, an indicator for assignment status and estimate IV regressions of outcomes of interest on expected inflation using T_{it} as instrument and pooling all waves of the survey so that time variation is now an additional relevant source of identifying variation[32]. However, inspection of the associated first stage regression

$$F_{it}\pi = \rho + \theta T_{it} + u_{it} \tag{11}$$

reveals that identification of the first stage effect and, in turn, of the effects of expected inflation rests essentially on the time variation of the signal rather than on the genuinely exogenous cross-sectional variation in expected inflation generated by the RCT. Comparisons of the expected values at time t conditional on assignment status of both sides of equation (11),

[32] Their specifications also include controls for observables and seasonal dummies. They also explore the possibility that the effects of expected inflation are delayed, augmenting the set of endogenous variables with further lags of $F\pi$ to be instrumented by the contemporaneous information treatment T. For expositional simplicity, I discuss without loss of generality a more basic specification abstracting from observables and lagged endogenous variables.

$E(F_{it}\pi|I_{it}=0,t)=\rho$ and $E(F_{it}\pi|I_{it}=1,t)=\rho+\theta\pi_t^*$, with their theoretical counterparts from equations (3) and (5), $E(F_{it}^0\pi|t)=\gamma E(\Pi_{it}^0|t)$ and $E(F_{it}^1\pi|t)=\gamma E(\Pi_{it}^0|t)+\gamma\omega(\pi_t^*-E(\Pi_{it}^0|t))$ shows that equation (11) is a valid representation of the relationship between the instrument and the inflation expectations of firms only if average firms' unobserved assessments of inflation prior to the signal are constant over time. Under this extreme implicit assumption the inflation rate presented to firms (or its deviation from an arbitrary constant value) comes always entirely as a surprise to informed firms so that a higher inflation rate presented to firms is always interpreted as an inflationary shock. However, this feature is clearly at odds with the data. On the one hand, average expectations of uninformed firms move largely in line with current inflation just like expectations of informed firms and Consensus forecasts (figure (1)); on the other, the fact that over time the response of average expected inflation to information assignment is both positive and negative, in a way largely unrelated to current inflation, is consistent with the fact that whether the assignment generates an inflationary shock crucially depends on prior expectations, which change over time[33]. In light of these considerations, their IV results offer little guidance to clarifying the role of expectations in shaping firms' decisions.

Overall, my findings cast doubts on the possibility of stimulating the real economy by directly shaping firms' inflation expectations through the timely provision of reliable information. The limits of this conclusion are obviously those of the external validity of my results. For example, in an environment of low and relatively stable inflation such as the one I study firms, who

[33]In Appendix (F) I present a visual intuition and a formal proof of this argument along with a decomposition of Coibion et al. (2020b)'s estimated effects into the underlying sources of identifying variation that shows that more than 80 percent of the value of the point estimate reflects the correlation over time between current inflation and the expectations of informed firms, and is thus unrelated with variation generated by the random provision of information. The remaining part reflects the difference between the mean expectations of informed and of uninformed firms over the entire sample period, and is thus unrelated to the specific piece of information randomly provided in each period.

appear to be relatively well informed, may choose not to adjust their prices because the revisions to their expected inflation induced by the additional information are overall limited, so that adjustment costs dominate; this might not be the case in higher or more volatile inflation environments populated with less informed firms where adequate communication policies might be more effective. If instead lack of causation reflects the failure to understand basic economic mechanisms, policies aimed at educating - rather than simply informing - the public would be more appropriate. Fortunately, surveys of firm and household expectations are being increasingly implemented that include experimental data collection to address policy-relevant macroeconomic questions. This will support and stimulate the much needed further research. To this end, however, I have shown that in order to support credible causal inference the use of data collected through experimental research designs requires a careful and deeper consideration of the underlying economic and econometric theoretical frameworks.

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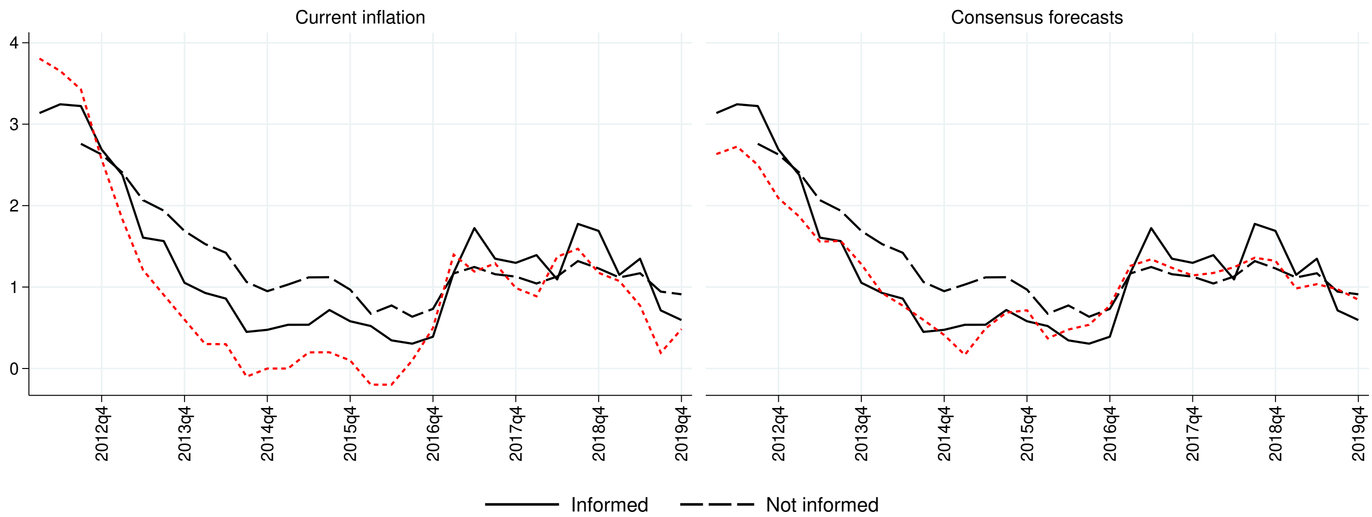
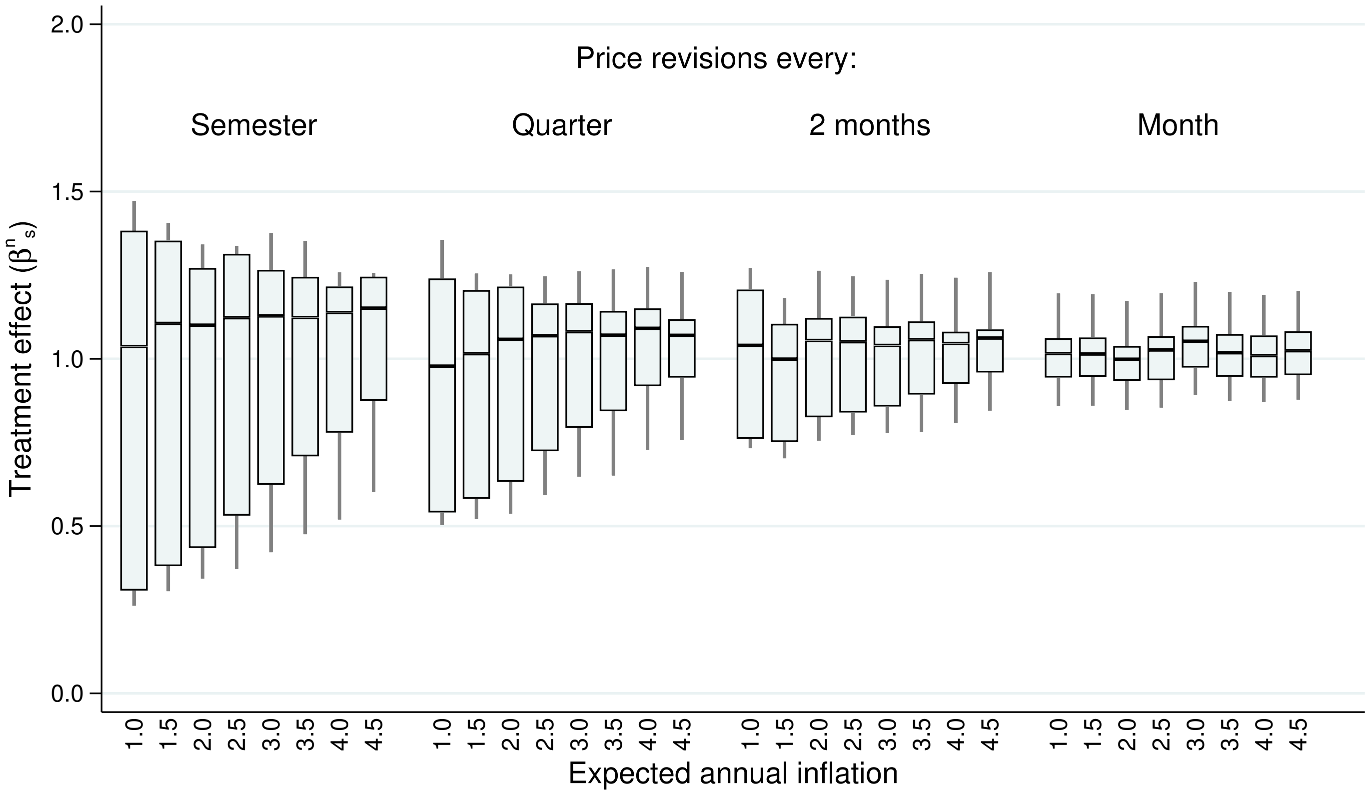
Figure 1: Firms' and consensus expected inflation and current inflation.



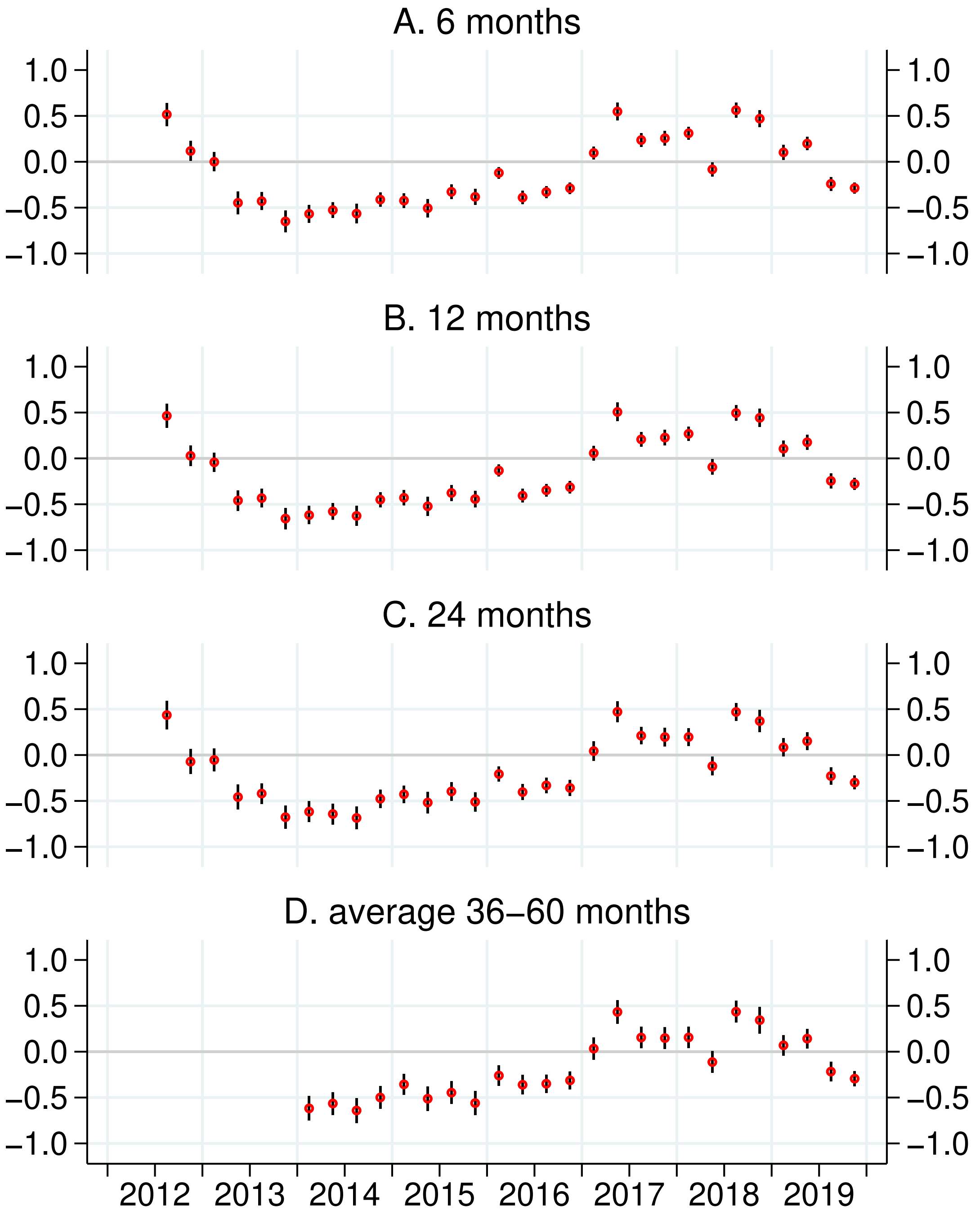
Note: The figure displays average one-year ahead expected inflation of firms presented with current inflation data (informed) and firms not presented with it (not informed) together with the inflation rate presented to firms (left-hand panel) and the Consensus Forecast one-year ahead expected inflation (right-hand panel).

Figure 2: The distribution of treatment effects.



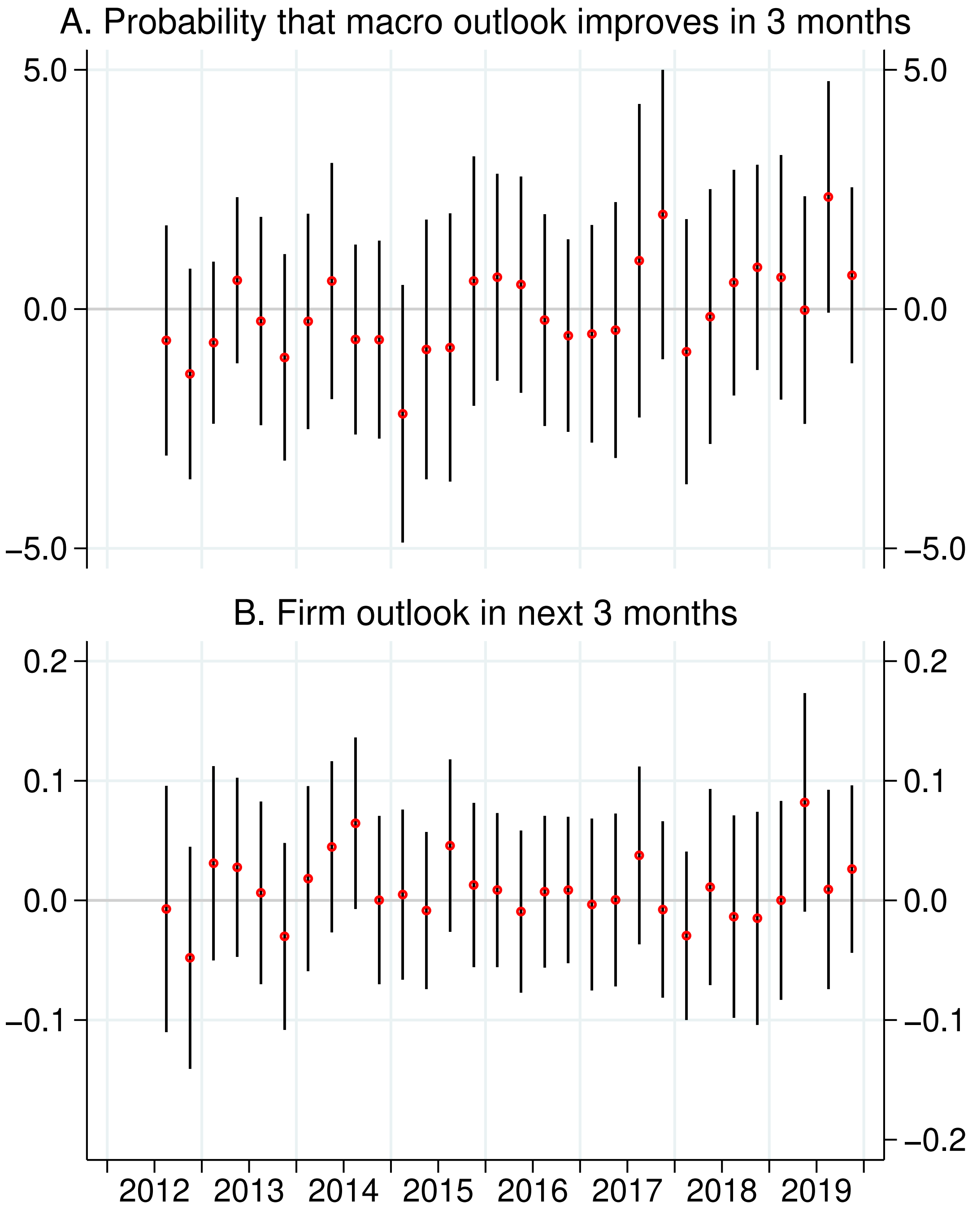
Note: The figure displays the distribution of the effect of a half percentage point increase in expected inflation on the expected change in own prices generated by the menu cost model in Nakamura and Steinsson (2008) solved under alternative values of underlying expected inflation and number of price revisions per year. Thin bars represent the range of treatment effects generated by the simulation; thick boxes represent the 10th-90th percentile of the effects; the horizontal line represents the median values. Statistics are computed on the steady-state distributions of the specific simulations.

Figure 3: Effects of information assignment on annual expected inflation.



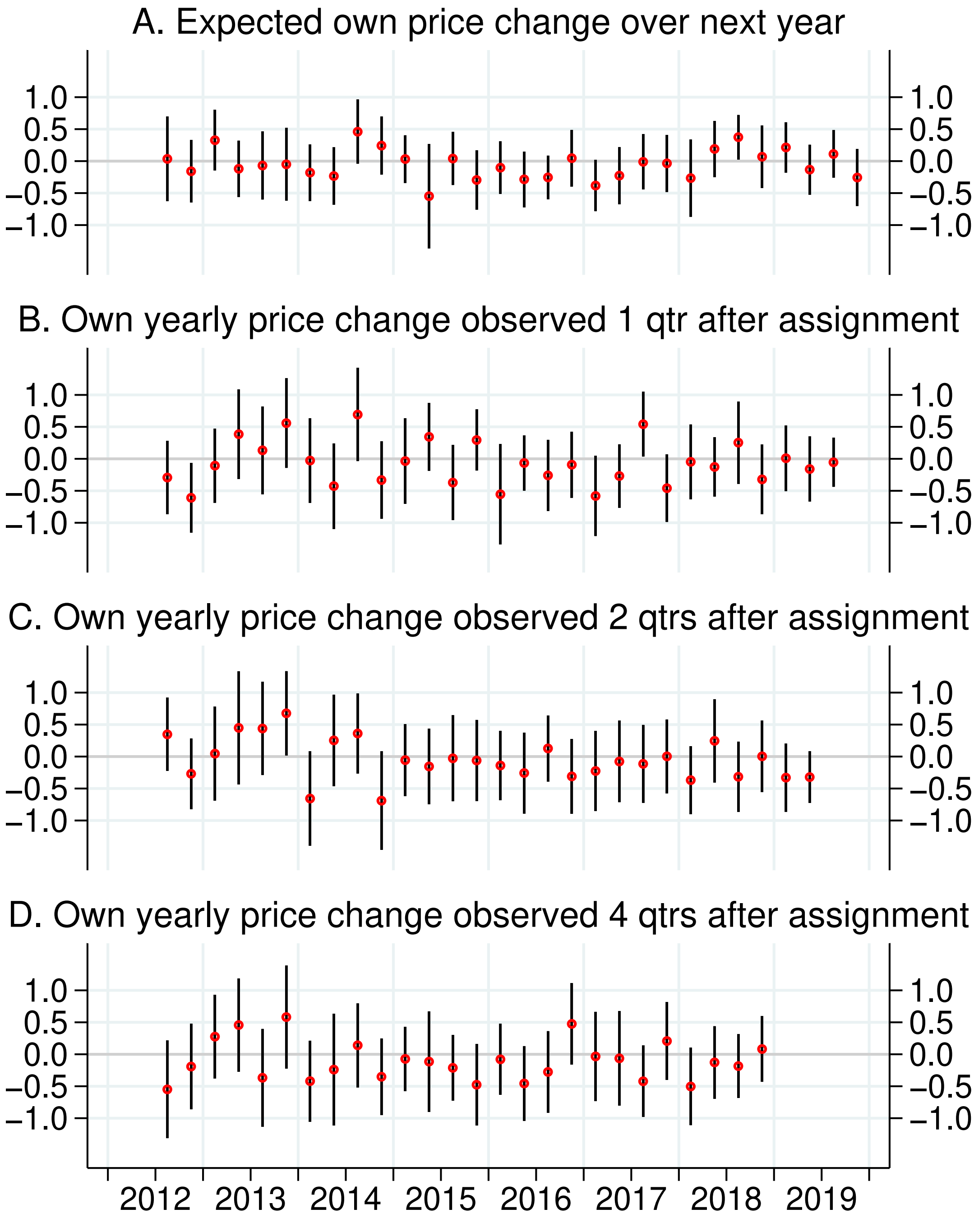
Source: Own elaborations of Bank of Italy Survey of Inflation and Growth Expectations. The figure displays the mean difference between expected inflation of informed and uninformed firms conditional on observable characteristics resulting from OLS estimation of equation (9) and 95 percent confidence regions based on Huber-White robust standard errors.

Figure 4: Effects of information assignment on qualitative assessments.



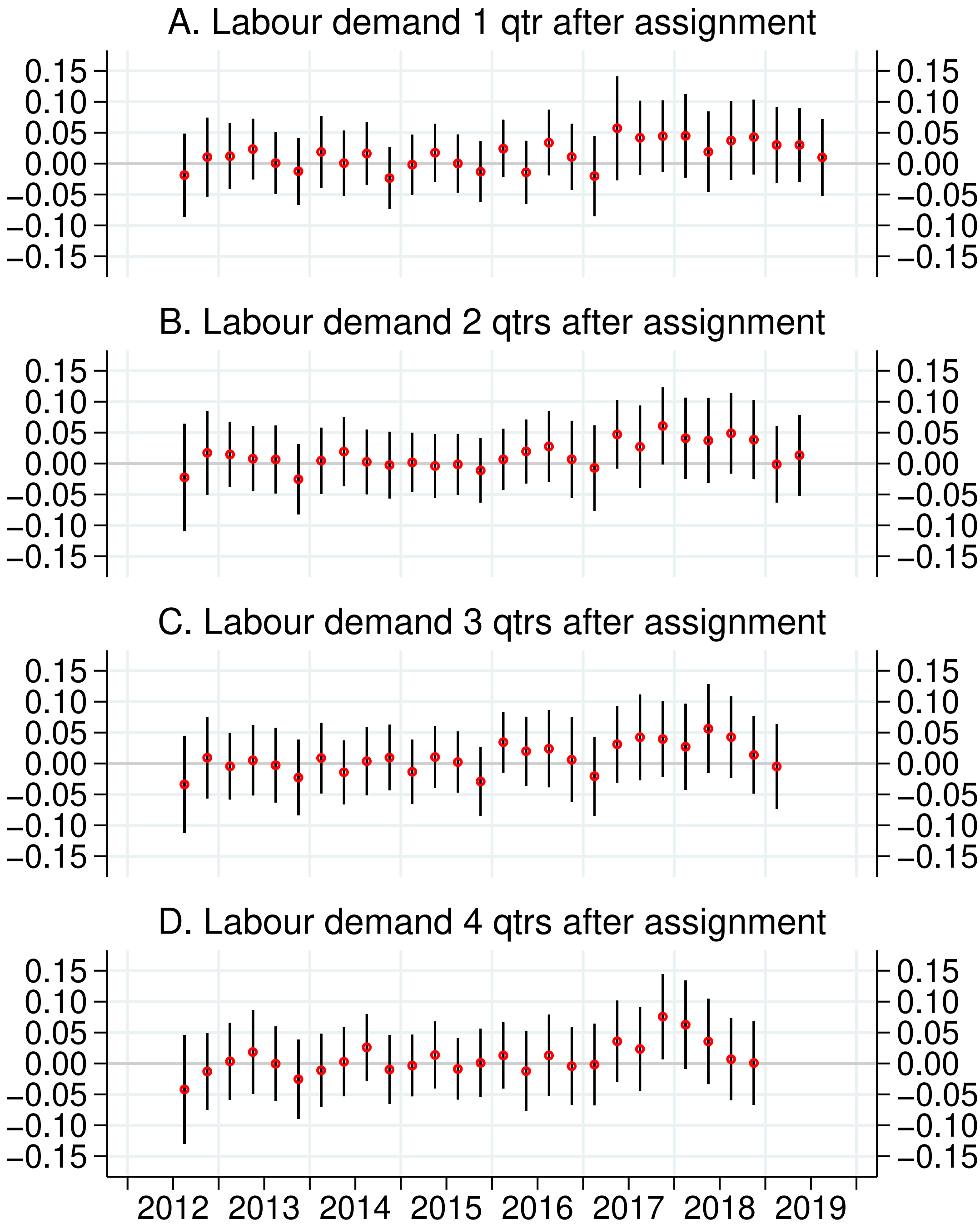
Source: Own elaborations of Bank of Italy Survey of Inflation and Growth Expectations. The figure displays the mean difference between qualitative assessments of informed and uninformed firms conditional on observable characteristics resulting from OLS estimation of equation (9) and 95 percent confidence regions based on Huber-White robust standard errors.

Figure 5: Effects of information assignment on own future price changes.



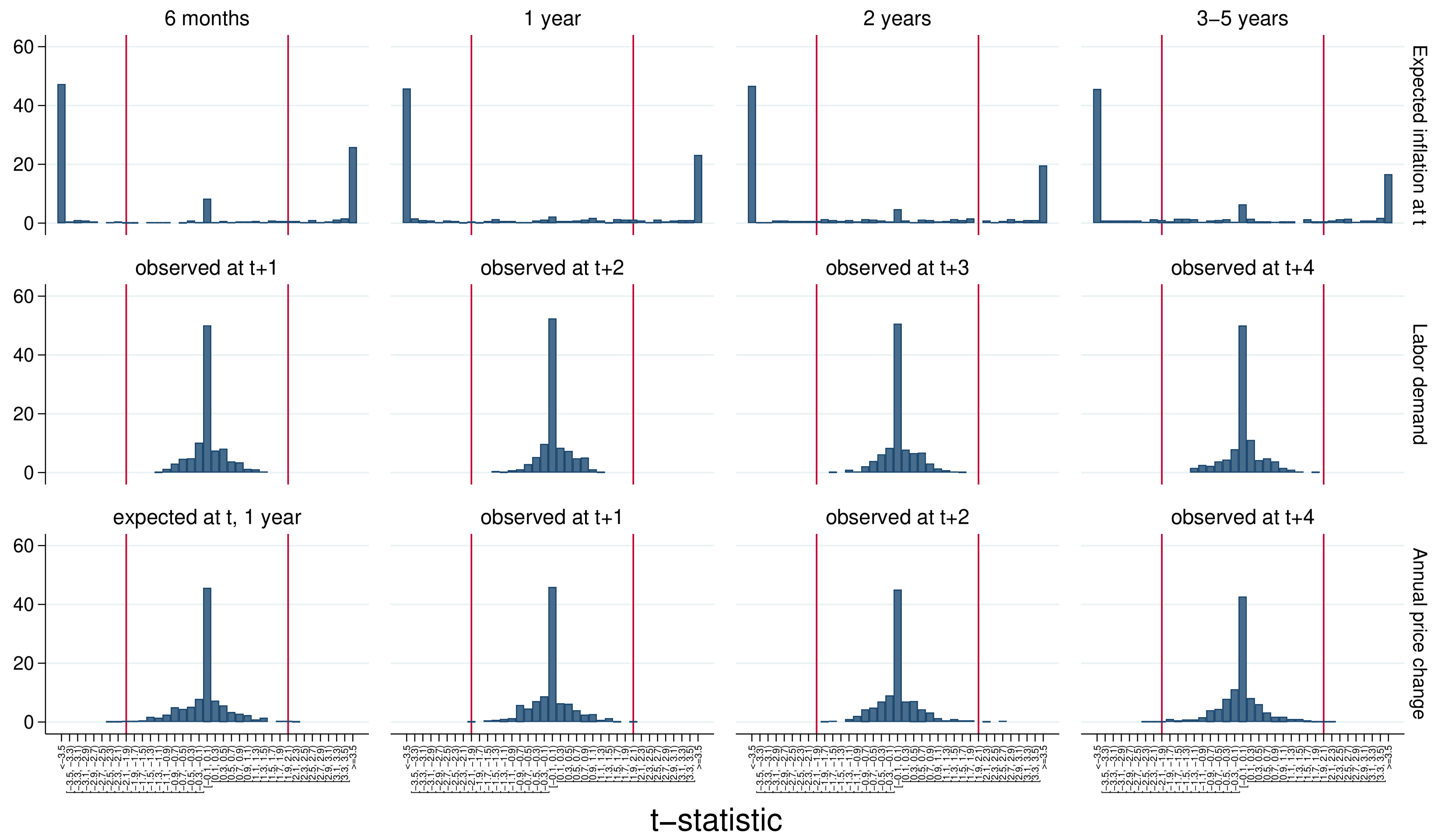
Source: Own elaborations of Bank of Italy Survey of Inflation and Growth Expectations. The figure displays the mean difference between expected and future price changes of informed and uninformed firms conditional on observable characteristics resulting from OLS estimation of equation (9) and 95 percent confidence regions based on Huber-White robust standard errors.

Figure 6: Effects of information assignment on future labour demand.



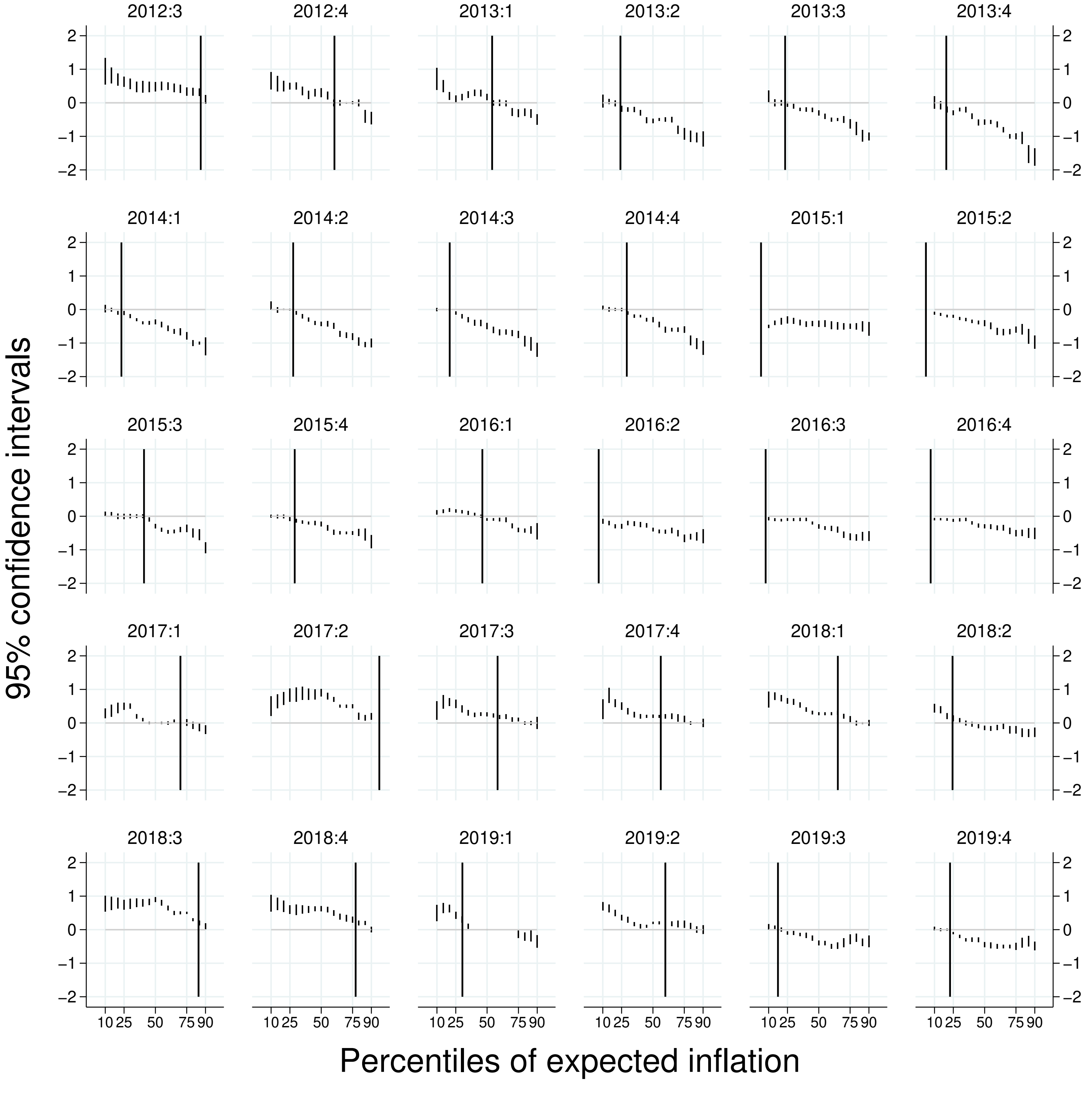
Source: Own elaborations of Bank of Italy Survey of Inflation and Growth Expectations. The figure displays the mean difference between future labour demand of informed and uninformed firms conditional on observable characteristics resulting from OLS estimation of equation (9) and 95 percent confidence regions based on Huber-White robust standard errors.

Figure 7: Distribution of t-statistics of QR estimates of the effect of information assignment.



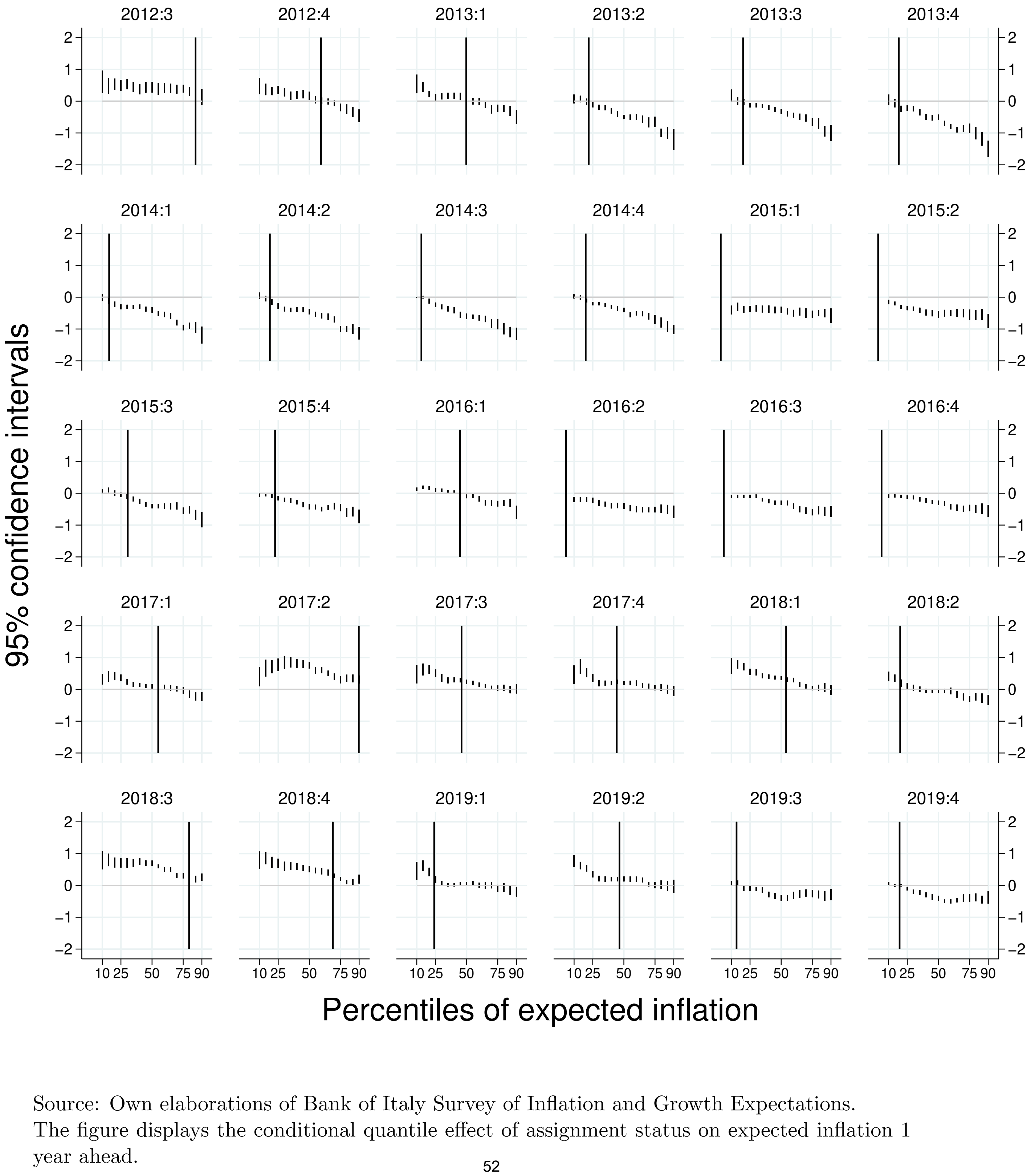
Source: Own elaborations of Bank of Italy Survey of Inflation and Growth Expectations. The figure displays the distribution of the t-statistics associated to point estimates of the conditional quantile effect of assignment status on the variable of interest. First row: expected inflation at various horizons collected at time t; second row: labour demand at subsequent quarters; third row: expected price change at time t and observed price changes at subsequent quarters.

Figure 8: Quantile regressions: Expected inflation in 6 months and exposure to information.



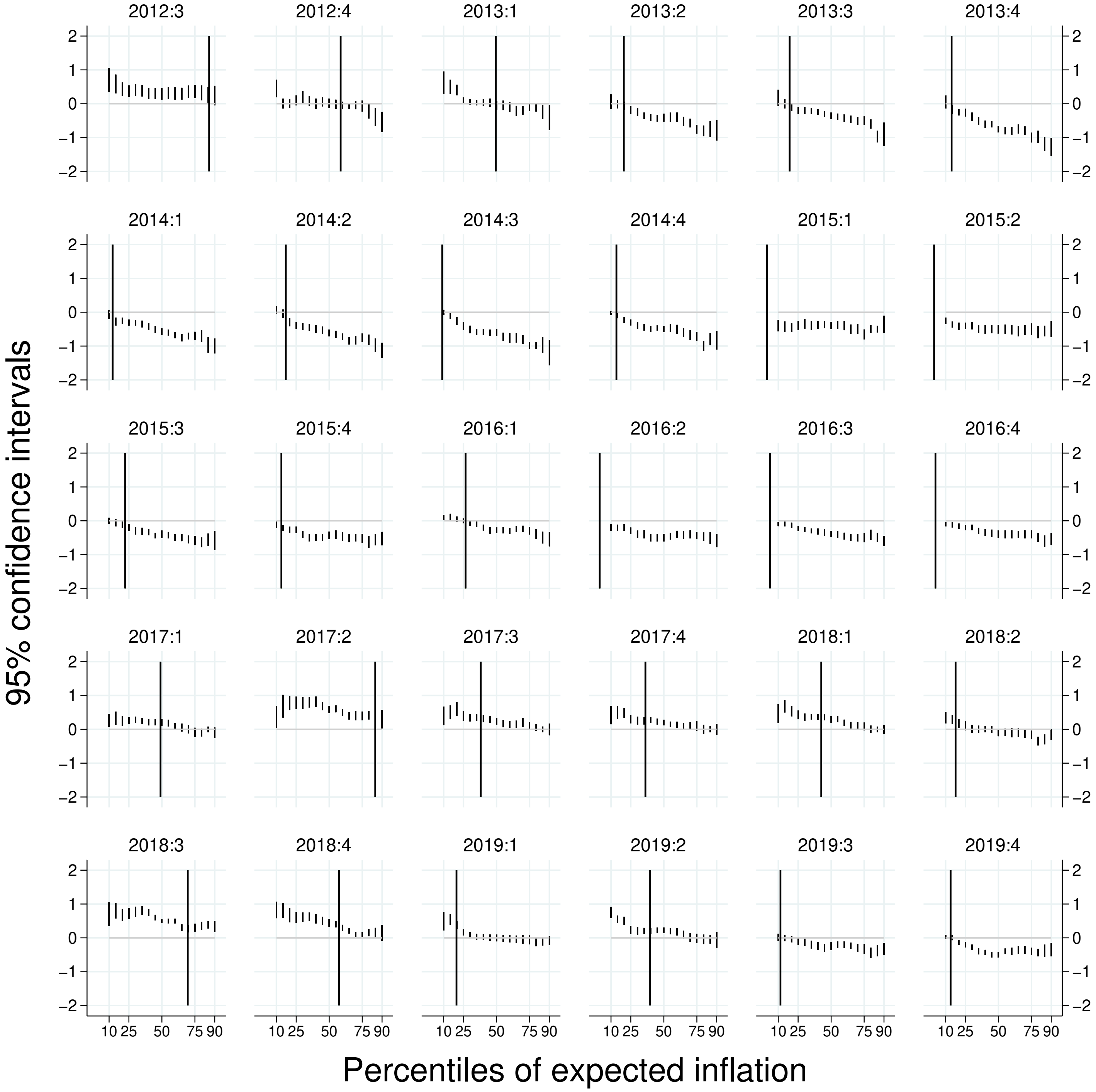
Source: Own elaborations of Bank of Italy Survey of Inflation and Growth Expectations.
The figure displays the conditional quantile effect of assignment status on expected inflation 6 months ahead.

Figure 9: Quantile regressions: Expected inflation in 1 year and exposure to information.



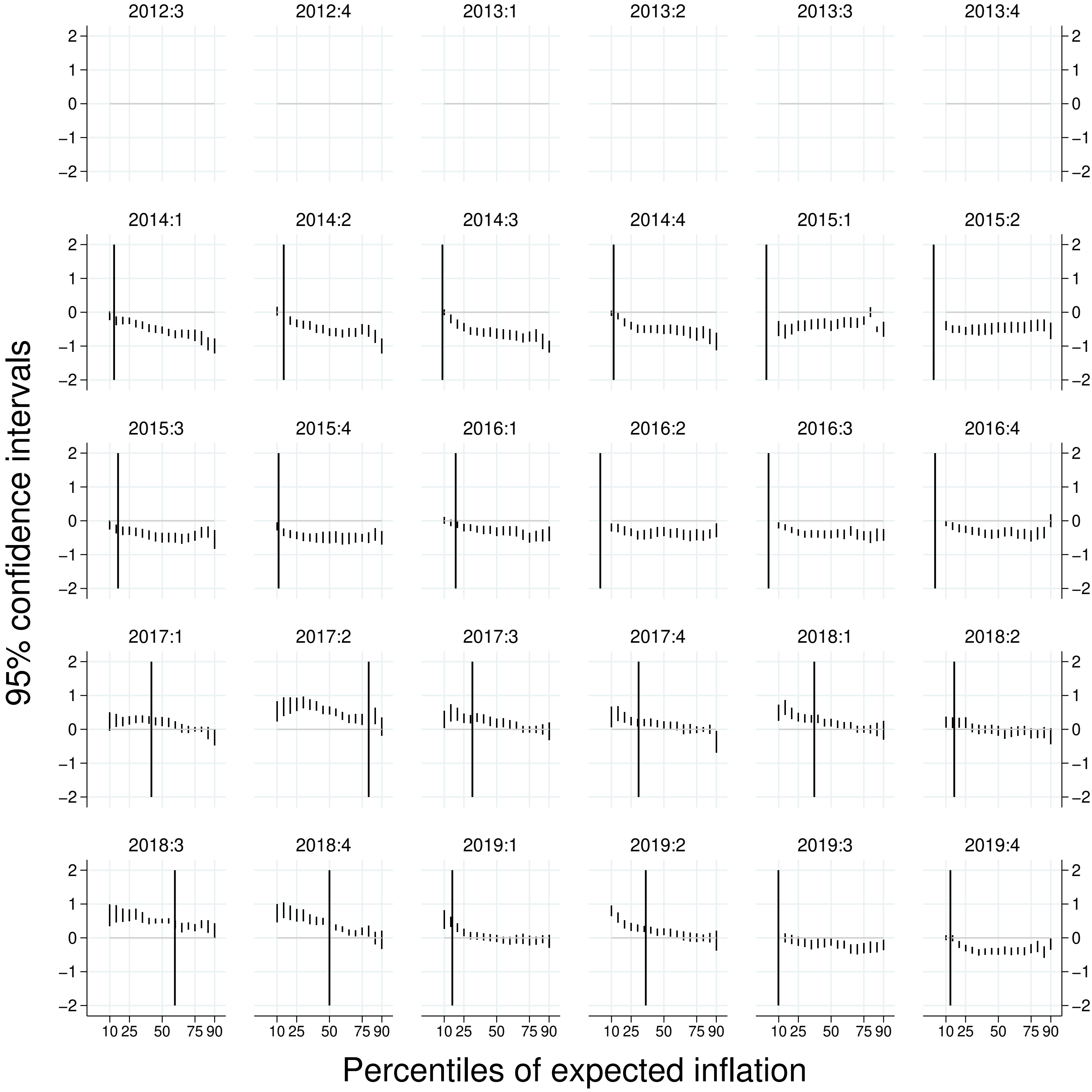
Source: Own elaborations of Bank of Italy Survey of Inflation and Growth Expectations.
The figure displays the conditional quantile effect of assignment status on expected inflation 1 year ahead.

Figure 10: Quantile regressions: Expected inflation in 2 years and exposure to information.



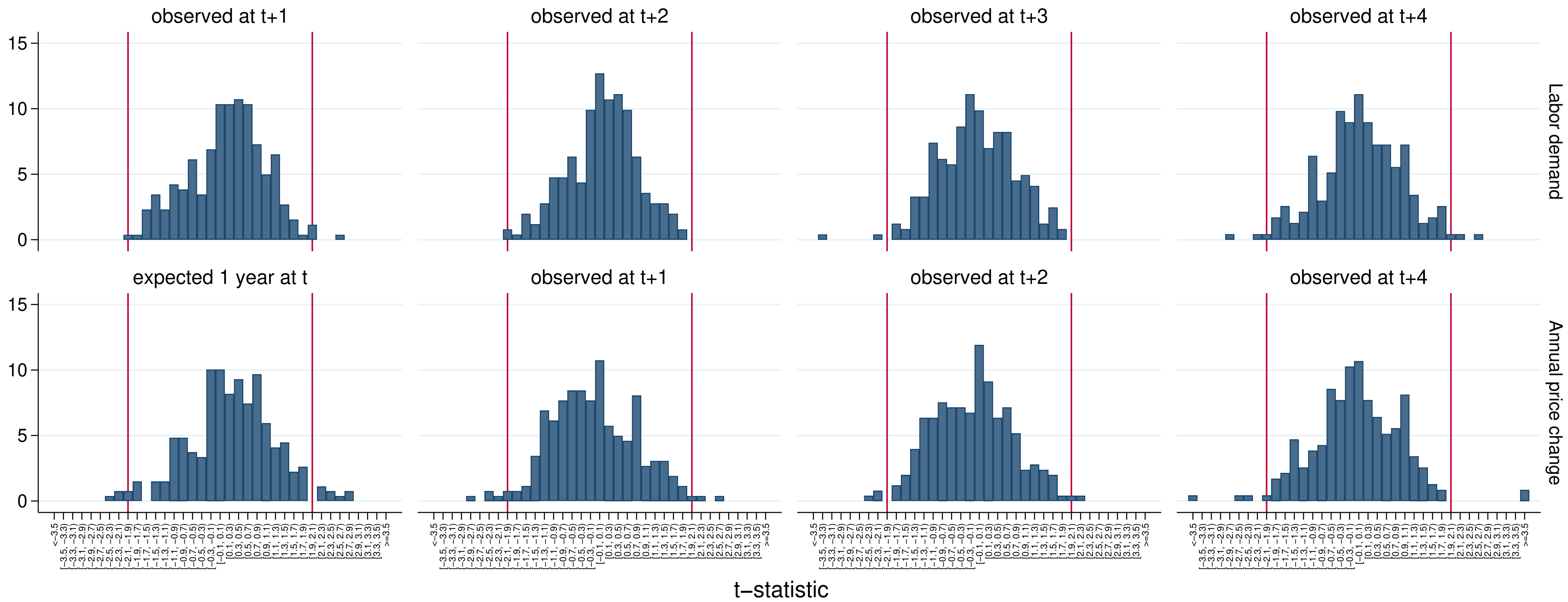
Source: Own elaborations of Bank of Italy Survey of Inflation and Growth Expectations.
The figure displays the conditional quantile effect of assignment status on expected inflation 2 years ahead.

Figure 11: Quantile regressions: Expected inflation in 3-5 years and exposure to information.



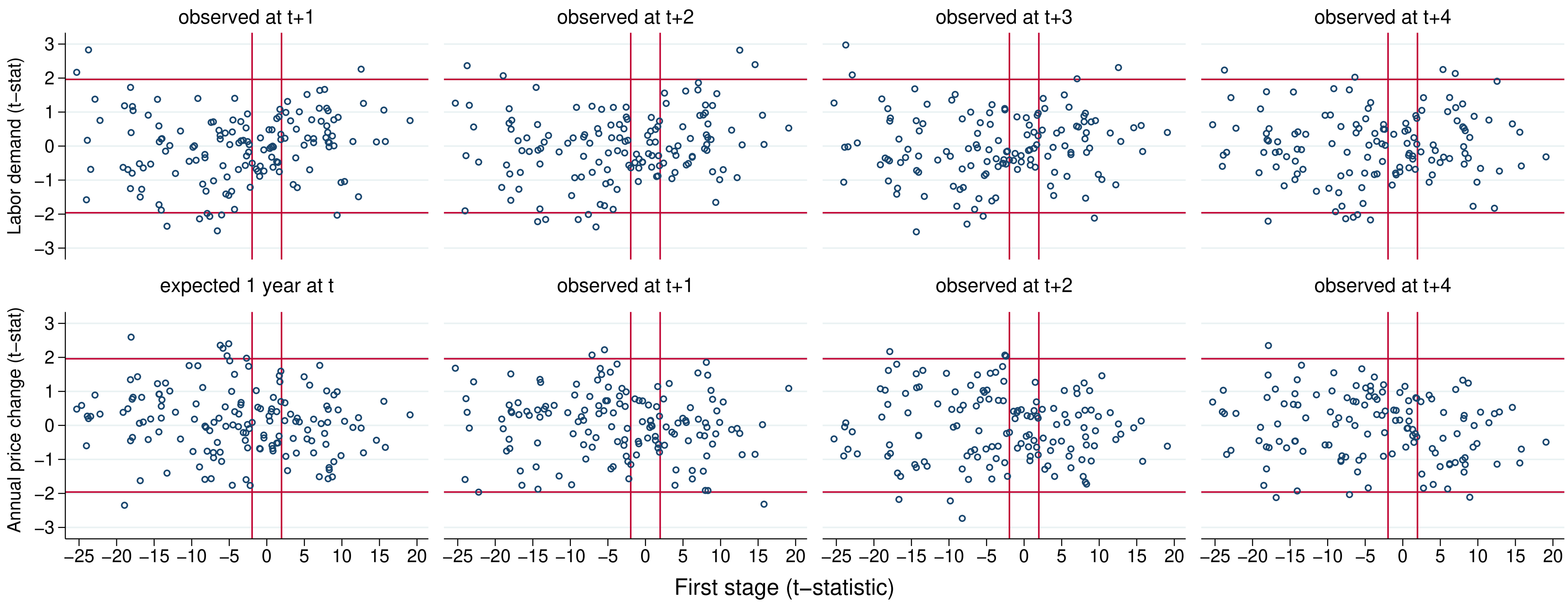
Source: Own elaborations of Bank of Italy Survey of Inflation and Growth Expectations.
The figure displays the conditional quantile effect of assignment status on average expected inflation between 3 and 5 years ahead.

Figure 12: Distribution of t-statistics of IVQR estimates of the effect of one year ahead expected inflation.



Source: Own elaborations of Bank of Italy Survey of Inflation and Growth Expectations. The figure displays the distribution of the t-statistics of IVQR estimates of the effect of one year ahead expected inflation on the variable of interest. Vertical lines correspond to ± 1.96.

Figure 13: T-statistics of local IV and first stage estimates.



Source: Own elaborations of Bank of Italy Survey of Inflation and Growth Expectations. The figure displays the t-statistic of local IV estimates of the effects of one year ahead expected inflation on the variable of interest (y-axis) against the t-statistic of the local first stage effect of assignment status on expected inflation. Vertical and horizontal lines correspond to ± 1.96.

Table 1: Non linear treatment effects

	Coeff. of variation of β_s^n				
Annual price reviews	min	10th	50th	90th	max
2	0.012	0.020	0.073	0.347	0.408
4	0.016	0.027	0.062	0.221	0.271
6	0.012	0.026	0.050	0.118	0.150
12	0.012	0.014	0.017	0.023	0.029

Note: The table reports statistics of the distribution across firms of the ratio between the within-firm standard deviation and the firm-specific mean of $\beta_s^n(\pi)$ generated by the model for $\pi \in \{0.01, 0.015, \ldots, 0.045, 0.05\}$.

Table 2: IV2SLS: own price change and expected inflation.

Dep. var.	(a) $E_t \Delta p_{t+4}$		(b) Δp_{t+1}		(c) Δp_{t+2}		(d) Δp_{t+4}	
	β	SE	β	SE	β	SE	β	SE
2012q3	0.08	0.719	-0.68	0.687	0.76	0.651	-1.44	1.062
2012q4	-5.50	14.787	-15.00	23.702	-4.52	6.650	-8.91	29.828
2013q1	-7.54	10.520	1.55	4.576	-0.78	6.427	-17.38	66.945
2013q2	0.26	0.487	-0.81	0.750	-0.94	0.935	-0.94	0.754
2013q3	0.16	0.622	-0.28	0.723	-1.03	0.878	0.67	0.706
2013q4	0.08	0.438	-0.87	0.563	-1.03**	0.518	-0.99	0.700
2014q1	0.29	0.362	0.05	0.576	0.99*	0.570	0.67	0.515
2014q2	0.40	0.393	0.66	0.518	-0.43	0.620	0.41	0.759
2014q3	-0.74*	0.412	-1.09*	0.584	-0.57	0.502	-0.21	0.489
2014q4	-0.54	0.520	0.70	0.642	1.54*	0.879	0.73	0.631
2015q1	-0.08	0.439	0.08	0.772	0.12	0.624	0.17	0.592
2015q2	1.05	0.796	-0.65	0.512	0.28	0.530	0.21	0.733
2015q3	-0.11	0.557	0.97	0.775	0.07	0.860	0.56	0.689
2015q4	0.67	0.533	-0.70	0.585	0.15	0.775	1.10	0.754
2016q1	0.77	1.576	4.45	3.482	1.20	2.363	0.58	2.082
2016q2	0.70	0.546	0.15	0.505	0.61	0.752	1.13	0.751
2016q3	0.73	0.497	0.71	0.770	-0.36	0.733	0.86	1.012
2016q4	-0.15	0.712	0.27	0.766	0.92	0.890	-1.48	1.011
2017q1	-6.63	5.911	-18.42	32.903	-3.44	5.240	-1.14	11.896
2017q2	-0.45	0.448	-0.53	0.486	-0.15	0.616	-0.14	0.833
2017q3	-0.05	1.048	2.40*	1.251	-0.55	1.477	-1.87	1.259
2017q4	-0.15	0.991	-1.98	1.213	0.01	1.385	1.00	1.524
2018q1	-0.99	1.149	-0.17	1.088	-1.41	1.027	-2.01	1.278
2018q2	-2.04	2.548	1.51	2.984	-3.37	5.025	2.99	7.801
2018q3	0.76**	0.355	0.53	0.671	-0.63	0.561	-0.40	0.546
2018q4	0.16	0.558	-0.78	0.689	0.01	0.723	0.20	0.614
2019q1	2.02	2.035	0.10	2.599	-5.70	6.851		
2019q2	-0.76	1.143	-0.89	1.472	-1.60	1.068		
2019q3	-0.46	0.773	0.24	0.877				
2019q4	0.92	0.816						

(*) p-value < 0.1; (**) p-value < 0.05; (***) p-value < 0.01. Robust standard errors.
Dependent variables: expected one-year ahead annual own price change reported in the same quarter of information assignment (col. a), annual own price change observed one (col. b), two (col. c), four (col. d) quarters after information assignment.
Control variables: past own price change, dummies for firm size, sector of activity, geographical area. Unweighted IV2SLS regressions.

Table 3: IV2SLS: labour demand and expected inflation.

	(a)		(b)		(c)		(d)	
Dep. var.	L_{t+1}		L_{t+2}		L_{t+3}		L_{t+4}	
	β	SE	β	SE	β	SE	β	SE
2012q3	-0.04	0.078	-0.05	0.095	-0.09	0.099	-0.11	0.116
2012q4	0.26	0.908	0.29	0.668	0.33	1.438	-0.60	2.242
2013q1	-0.18	0.415	-0.25	0.530	0.11	0.688	-0.22	2.099
2013q2	-0.05	0.053	-0.02	0.056	-0.01	0.056	-0.04	0.071
2013q3	-0.00	0.053	-0.02	0.065	0.01	0.066	0.00	0.056
2013q4	0.02	0.042	0.04	0.043	0.03	0.045	0.04	0.055
2014q1	-0.03	0.051	-0.01	0.041	-0.02	0.049	0.02	0.048
2014q2	-0.00	0.041	-0.03	0.048	0.02	0.043	-0.00	0.048
2014q3	-0.03	0.040	-0.00	0.041	-0.01	0.043	-0.04	0.040
2014q4	0.05	0.053	0.01	0.061	-0.02	0.059	0.02	0.059
2015q1	0.00	0.056	-0.00	0.053	0.03	0.061	0.01	0.059
2015q2	-0.03	0.045	0.01	0.046	-0.02	0.052	-0.03	0.051
2015q3	-0.00	0.062	0.00	0.063	-0.01	0.066	0.02	0.066
2015q4	0.03	0.060	0.03	0.064	0.07	0.064	-0.00	0.064
2016q1	-0.19	0.197	-0.06	0.214	-0.26	0.206	-0.10	0.203
2016q2	0.03	0.060	-0.05	0.062	-0.05	0.069	0.03	0.081
2016q3	-0.09	0.074	-0.08	0.082	-0.07	0.095	-0.04	0.104
2016q4	-0.03	0.080	-0.02	0.094	-0.02	0.113	0.01	0.098
2017q1	-0.64	1.510	-0.11	0.539	-0.54	1.129	-0.06	1.121
2017q2	0.11	0.084	0.09*	0.055	0.06	0.065	0.08	0.075
2017q3	0.19	0.141	0.13	0.166	0.24	0.204	0.10	0.152
2017q4	0.19	0.134	0.29*	0.167	0.19	0.161	0.37*	0.190
2018q1	0.17	0.129	0.16	0.129	0.10	0.127	0.25	0.152
2018q2	-0.23	0.421	-0.51	0.587	-0.81	0.788	-0.83	1.303
2018q3	0.08	0.067	0.10	0.066	0.09	0.069	0.01	0.072
2018q4	0.10	0.076	0.10	0.083	0.03	0.073	0.00	0.081
2019q1	0.30	0.350	-0.02	0.536	-0.05	0.331		
2019q2	0.17	0.175	0.07	0.165				
2019q3	-0.05	0.141						
2019q4								

(*) p-value < 0.1; (**) p-value < 0.05; (***) p-value < 0.01. Robust standard errors.
Dependent variables: (log) employment one (col. a), two (col. b), three (col. c), four (col. d) quarters after information assignment.
Control variables: past own price change, dummies for firm size, sector of activity, geographical area. Unweighted IV2SLS regressions.

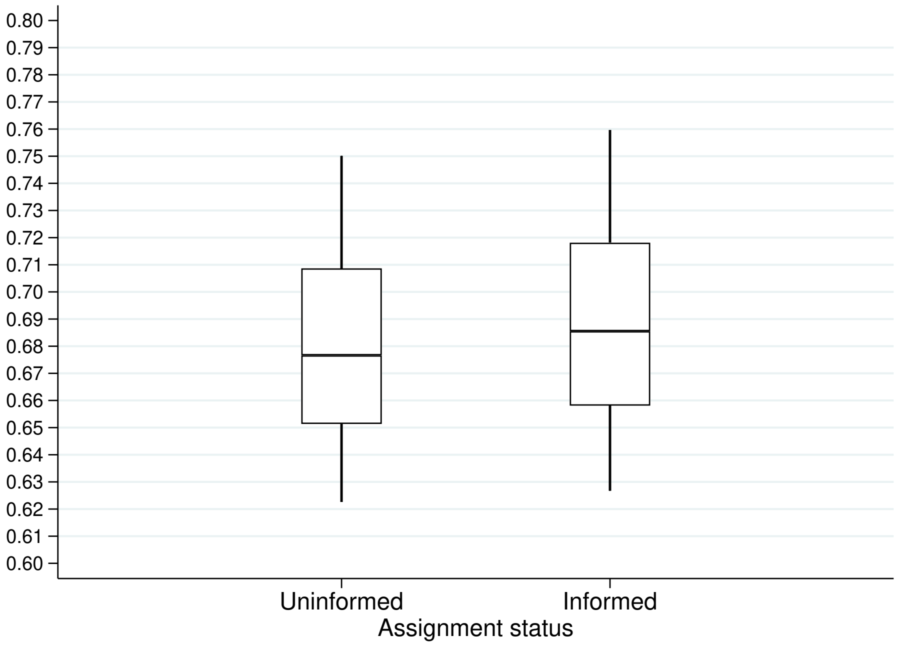
Appendices

Appendix A Randomness of assignment status

Two usual concerns with RCTs similar to that featured by the survey are that assignment is not truly random and that panel attrition may be related to assignment status. As to the first concern, I complement the evidence based on the same sample in Coibion et al. (2020b)'s Online Appendix Table 2 that shows that no specific observable characteristic is significantly related to assignment status. Specificaly, I follow the intuition of Rosenbaum and Rubin (1983) in addressing the issue of selection bias in evaluation studies based on observational data and estimate a probit model for being presented with inflaton data that includes a set of dummies for firm size, sector of activity and geographic area as well as time dummies. Figure (A.1), which displays the distribution of predicted probabilities of being presented with inflation data across observed assignment status, shows them to be substantially the same across the two groups, confirming that assignment status is not related to covariates.

As to the second concern, I again estimate a probit model for the probability of participating in the survey two and four quarters after assignment including actual assignment status, and a set of dummies for firm size, sector of activity and geographic area as well as time dummies. The point estimate (standard error) of the effect of assignment status on the probability of participating two quarters later is 0.009 (0.018) and of participating four quarters later is 0.014 (0.018), thus mitigating concerns that panel attrition is correlated with assignment status.

Figure A.1: Distribution of the estimated probability of being presented with inflation data



Source: Own elaborations of Bank of Italy Survey of Inflation and Growth Expectations.

Appendix B Reduced form results

Tables (B.1) to (B.12) complement the evidence presented in the paper. They report results for reduced form estimations of equation (9) in the main text on all dependent variables considered. Specifications are estimated under different sample selection criteria and both with and without sample weights. All estimates use Huber-White robust standard errors. Trimmed samples exclude observations with one-year-ahead expected inflation in the top and bottom 2 percent of the quarter- and assignment-specific cross-sectional distribution; untrimmed samples consider all available observations.

Sample weights are disseminated with the original dataset. They are computed by means of a two-step procedure. In a first step, a simple weight is computed as the inverse of the inclusion probability associated to each sampled unit. In a second step, a calibration procedure (raking) ensures that the sample estimates of the total number of firms in each stratum equals the actual number of firms in that stratum known from external sources. Sample strata are combinations of 4 geographic macroregions, 3 industries and 3 firm-size brackets.

Table B.1: Effect of information assignment on 6-months-ahead expected inflation.

	(a)		(b)		(c)		(d)	
Sample:	Trimmed				Untrimmed			
Weights:	No		Yes		No		Yes	
	Info	SE	Info	SE	Info	SE	Info	SE
2012q3	0.52***	0.064	0.58***	0.081	0.50***	0.073	0.55***	0.091
2012q4	0.12**	0.055	0.17**	0.070	0.16**	0.070	0.23***	0.081
2013q1	0.00	0.053	0.03	0.061	0.02	0.086	0.02	0.100
2013q2	-0.45***	0.063	-0.46***	0.071	-0.47***	0.078	-0.47***	0.084
2013q3	-0.43***	0.049	-0.46***	0.057	-0.41***	0.071	-0.42***	0.087
2013q4	-0.65***	0.060	-0.68***	0.067	-0.66***	0.082	-0.72***	0.105
2014q1	-0.57***	0.050	-0.59***	0.059	-0.55***	0.068	-0.55***	0.074
2014q2	-0.53***	0.044	-0.56***	0.052	-0.53***	0.070	-0.54***	0.079
2014q3	-0.57***	0.054	-0.59***	0.060	-0.55***	0.077	-0.55***	0.089
2014q4	-0.41***	0.040	-0.46***	0.048	-0.46***	0.051	-0.49***	0.060
2015q1	-0.42***	0.040	-0.42***	0.043	-0.47***	0.059	-0.46***	0.063
2015q2	-0.51***	0.051	-0.55***	0.061	-0.57***	0.077	-0.67***	0.098
2015q3	-0.33***	0.040	-0.34***	0.045	-0.37***	0.060	-0.38***	0.064
2015q4	-0.38***	0.045	-0.44***	0.062	-0.38***	0.069	-0.46***	0.079
2016q1	-0.12***	0.032	-0.11***	0.038	-0.16***	0.058	-0.17**	0.068
2016q2	-0.39***	0.037	-0.40***	0.045	-0.42***	0.059	-0.45***	0.064
2016q3	-0.33***	0.033	-0.35***	0.036	-0.31***	0.058	-0.34***	0.061
2016q4	-0.29***	0.031	-0.31***	0.037	-0.33***	0.044	-0.34***	0.050
2017q1	0.10***	0.035	0.07*	0.037	0.00	0.060	-0.04	0.068
2017q2	0.55***	0.049	0.50***	0.059	0.53***	0.065	0.44***	0.103
2017q3	0.24***	0.038	0.20***	0.046	0.21***	0.061	0.15*	0.086
2017q4	0.26***	0.041	0.23***	0.048	0.19***	0.066	0.13	0.087
2018q1	0.31***	0.036	0.29***	0.042	0.35***	0.048	0.35***	0.055
2018q2	-0.08**	0.039	-0.10**	0.047	-0.03	0.050	-0.04	0.057
2018q3	0.56***	0.041	0.58***	0.048	0.52***	0.067	0.52***	0.077
2018q4	0.47***	0.047	0.46***	0.056	0.47***	0.051	0.46***	0.060
2019q1	0.10**	0.042	0.06	0.051	0.02	0.062	0.02	0.057
2019q2	0.20***	0.037	0.22***	0.040	0.22***	0.052	0.24***	0.058
2019q3	-0.24***	0.038	-0.28***	0.047	-0.24***	0.049	-0.30***	0.060
2019q4	-0.29***	0.030	-0.31***	0.036	-0.31***	0.054	-0.38***	0.062

Huber-White robust standard errors. (*) p-value $<$ 0.1; (**) p-value $<$ 0.05; (***) p-value $<$ 0.01.

Dependent variable: expected 6-months-ahead inflation reported in the same quarter of information assignment.

The table reports the estimated coefficients on a dummy for having received information about current inflation obtained from period-by-period linear regressions of the dependent variable that also include sector dummies, area dummies, class size dummies and reported own price change over the last 12 months. Cols. (a) unweighted regression and (b) weighted regressions, sample excludes observations in the top and bottom 2 percent of the period-specific and information assignment-specific distribution of reported expected inflation; cols. (c) unweighted regression and (d) weighted regressions, sample includes all observations.

Table B.2: Effect of information assignment on 1-year-ahead expected inflation.

	(a)		(b)		(c)		(d)	
Sample:	Trimmed				Untrimmed			
Weights:	No		Yes		No		Yes	
	Info	SE	Info	SE	Info	SE	Info	SE
2012q3	0.46***	0.067	0.50***	0.089	0.43***	0.082	0.45***	0.109
2012q4	0.03	0.057	0.07	0.073	0.08	0.072	0.15*	0.087
2013q1	-0.04	0.053	-0.05	0.060	-0.02	0.084	-0.03	0.093
2013q2	-0.46***	0.057	-0.49***	0.064	-0.47***	0.073	-0.45***	0.084
2013q3	-0.43***	0.052	-0.47***	0.060	-0.39***	0.068	-0.39***	0.082
2013q4	-0.66***	0.059	-0.66***	0.069	-0.65***	0.085	-0.67***	0.116
2014q1	-0.62***	0.050	-0.65***	0.058	-0.61***	0.068	-0.62***	0.076
2014q2	-0.58***	0.046	-0.60***	0.054	-0.58***	0.068	-0.58***	0.077
2014q3	-0.63***	0.055	-0.66***	0.061	-0.60***	0.079	-0.61***	0.094
2014q4	-0.45***	0.041	-0.50***	0.051	-0.48***	0.052	-0.51***	0.063
2015q1	-0.43***	0.042	-0.46***	0.047	-0.50***	0.068	-0.52***	0.067
2015q2	-0.52***	0.053	-0.60***	0.068	-0.58***	0.078	-0.71***	0.103
2015q3	-0.38***	0.044	-0.39***	0.050	-0.41***	0.065	-0.43***	0.072
2015q4	-0.44***	0.046	-0.52***	0.062	-0.39***	0.079	-0.49***	0.087
2016q1	-0.13***	0.033	-0.11***	0.038	-0.16***	0.055	-0.16***	0.060
2016q2	-0.41***	0.038	-0.45***	0.044	-0.43***	0.059	-0.49***	0.064
2016q3	-0.35***	0.035	-0.39***	0.039	-0.33***	0.058	-0.37***	0.059
2016q4	-0.31***	0.035	-0.35***	0.040	-0.34***	0.047	-0.36***	0.052
2017q1	0.06	0.041	0.03	0.044	0.02	0.058	-0.01	0.060
2017q2	0.51***	0.051	0.47***	0.063	0.50***	0.069	0.43***	0.106
2017q3	0.21***	0.040	0.18***	0.051	0.19***	0.062	0.14	0.088
2017q4	0.23***	0.044	0.21***	0.052	0.16**	0.072	0.11	0.090
2018q1	0.27***	0.039	0.25***	0.045	0.34***	0.051	0.33***	0.060
2018q2	-0.09**	0.043	-0.13**	0.053	-0.03	0.056	-0.06	0.069
2018q3	0.49***	0.043	0.50***	0.050	0.46***	0.072	0.45***	0.082
2018q4	0.44***	0.051	0.43***	0.061	0.44***	0.057	0.43***	0.067
2019q1	0.11**	0.045	0.07	0.055	0.03	0.065	0.03	0.064
2019q2	0.18***	0.041	0.18***	0.048	0.18***	0.068	0.21***	0.074
2019q3	-0.24***	0.042	-0.30***	0.053	-0.23***	0.053	-0.31***	0.066
2019q4	-0.28***	0.033	-0.31***	0.040	-0.31***	0.062	-0.38***	0.069

Huber-White robust standard errors. (*) p-value < 0.1; (**) p-value < 0.05; (***) p-value < 0.01.

Dependent variable: expected 12-months-ahead inflation reported in the same quarter of information assignment.

The table reports the estimated coefficients on a dummy for having received information about current inflation obtained from period-by-period linear regressions of the dependent variable that also include sector dummies, area dummies, class size dummies and reported own price change over the last 12 months. Cols. (a) unweighted regression and (b) weighted regressions, sample excludes observations in the top and bottom 2 percent of the period-specific and information assignment-specific distribution of reported expected inflation; cols. (c) unweighted regression and (d) weighted regressions, sample includes all observations.

Table B.3: Effect of information assignment on 2-year-ahead expected inflation.

	(a)		(b)		(c)		(d)	
Sample:	Trimmed				Untrimmed			
Weights:	No		Yes		No		Yes	
	Info	SE	Info	SE	Info	SE	Info	SE
2012q3	0.44***	0.079	0.46***	0.105	0.42***	0.088	0.42***	0.119
2012q4	-0.07	0.069	-0.06	0.089	-0.02	0.082	0.01	0.100
2013q1	-0.05	0.064	-0.06	0.071	-0.03	0.089	-0.05	0.099
2013q2	-0.46***	0.069	-0.48***	0.080	-0.45***	0.081	-0.43***	0.095
2013q3	-0.42***	0.057	-0.43***	0.063	-0.36***	0.070	-0.34***	0.081
2013q4	-0.68***	0.065	-0.70***	0.078	-0.68***	0.079	-0.72***	0.105
2014q1	-0.62***	0.058	-0.67***	0.064	-0.63***	0.076	-0.66***	0.081
2014q2	-0.64***	0.058	-0.67***	0.069	-0.63***	0.074	-0.63***	0.086
2014q3	-0.69***	0.063	-0.74***	0.070	-0.71***	0.077	-0.73***	0.093
2014q4	-0.48***	0.051	-0.53***	0.062	-0.51***	0.058	-0.53***	0.070
2015q1	-0.43***	0.048	-0.46***	0.055	-0.50***	0.072	-0.53***	0.072
2015q2	-0.52***	0.060	-0.62***	0.082	-0.59***	0.080	-0.75***	0.108
2015q3	-0.40***	0.052	-0.39***	0.065	-0.44***	0.070	-0.45***	0.084
2015q4	-0.51***	0.054	-0.60***	0.069	-0.46***	0.083	-0.57***	0.092
2016q1	-0.21***	0.041	-0.21***	0.049	-0.20***	0.060	-0.20***	0.066
2016q2	-0.40***	0.044	-0.46***	0.051	-0.42***	0.061	-0.48***	0.067
2016q3	-0.33***	0.043	-0.37***	0.047	-0.30***	0.062	-0.34***	0.061
2016q4	-0.36***	0.045	-0.40***	0.049	-0.39***	0.054	-0.42***	0.058
2017q1	0.04	0.054	0.00	0.062	-0.01	0.072	-0.04	0.079
2017q2	0.47***	0.058	0.47***	0.070	0.48***	0.074	0.45***	0.110
2017q3	0.21***	0.048	0.19***	0.060	0.19***	0.067	0.15*	0.092
2017q4	0.20***	0.051	0.17***	0.060	0.10	0.084	0.05	0.099
2018q1	0.20***	0.049	0.20***	0.057	0.27***	0.059	0.28***	0.068
2018q2	-0.12**	0.052	-0.17***	0.063	-0.04	0.064	-0.06	0.078
2018q3	0.47***	0.050	0.49***	0.058	0.43***	0.082	0.43***	0.091
2018q4	0.37***	0.062	0.36***	0.073	0.38***	0.066	0.36***	0.077
2019q1	0.08*	0.051	0.06	0.061	0.01	0.069	0.02	0.071
2019q2	0.15***	0.049	0.15**	0.057	0.18**	0.074	0.18**	0.080
2019q3	-0.23***	0.048	-0.29***	0.055	-0.22***	0.061	-0.29***	0.070
2019q4	-0.30***	0.038	-0.34***	0.045	-0.29***	0.061	-0.37***	0.070

Huber-White robust standard errors. (*) p-value < 0.1; (**) p-value < 0.05; (***) p-value < 0.01.

Dependent variable: expected 24-months-ahead inflation reported in the same quarter of information assignment.

The table reports the estimated coefficients on a dummy for having received information about current inflation obtained from period-by-period linear regressions of the dependent variable that also include sector dummies, area dummies, class size dummies and reported own price change over the last 12 months. Cols. (a) unweighted regression and (b) weighted regressions, sample excludes observations in the top and bottom 2 percent of the period-specific and information assignment-specific distribution of reported expected inflation; cols. (c) unweighted regression and (d) weighted regressions, sample includes all observations.

Table B.4: Effect of information assignment on average expected inflation 3-5 years ahead.

	(a)		(b)		(c)		(d)	
Sample:	Trimmed				Untrimmed			
Weights:	No		Yes		No		Yes	
	Info	SE	Info	SE	Info	SE	Info	SE
2012q3								
2012q4								
2013q1								
2013q2								
2013q3								
2013q4								
2014q1	-0.62***	0.068	-0.69***	0.077	-0.61***	0.081	-0.66***	0.087
2014q2	-0.56***	0.063	-0.60***	0.076	-0.57***	0.080	-0.58***	0.094
2014q3	-0.64***	0.069	-0.72***	0.079	-0.68***	0.083	-0.74***	0.100
2014q4	-0.50***	0.063	-0.55***	0.077	-0.51***	0.068	-0.53***	0.084
2015q1	-0.36***	0.058	-0.40***	0.069	-0.44***	0.076	-0.47***	0.081
2015q2	-0.51***	0.068	-0.65***	0.095	-0.56***	0.081	-0.75***	0.112
2015q3	-0.45***	0.063	-0.49***	0.071	-0.50***	0.078	-0.57***	0.086
2015q4	-0.56***	0.067	-0.68***	0.100	-0.50***	0.091	-0.64***	0.117
2016q1	-0.26***	0.058	-0.32***	0.069	-0.24***	0.072	-0.30***	0.083
2016q2	-0.36***	0.054	-0.42***	0.065	-0.37***	0.065	-0.43***	0.075
2016q3	-0.35***	0.051	-0.39***	0.055	-0.33***	0.073	-0.36***	0.074
2016q4	-0.31***	0.050	-0.37***	0.060	-0.33***	0.062	-0.37***	0.071
2017q1	0.03	0.062	0.00	0.070	0.01	0.075	-0.01	0.083
2017q2	0.43***	0.065	0.44***	0.078	0.45***	0.080	0.42***	0.114
2017q3	0.15***	0.060	0.18**	0.072	0.12	0.076	0.14	0.101
2017q4	0.15**	0.060	0.18**	0.069	0.05	0.090	0.05	0.105
2018q1	0.16***	0.059	0.16**	0.068	0.25***	0.068	0.26***	0.078
2018q2	-0.11*	0.060	-0.13*	0.067	-0.03	0.070	-0.03	0.082
2018q3	0.44***	0.060	0.46***	0.072	0.38***	0.087	0.39***	0.099
2018q4	0.34***	0.074	0.35***	0.085	0.34***	0.077	0.34***	0.088
2019q1	0.07	0.057	0.03	0.068	-0.00	0.073	-0.00	0.078
2019q2	0.14***	0.054	0.13**	0.062	0.18**	0.073	0.17**	0.081
2019q3	-0.22***	0.055	-0.26***	0.069	-0.21***	0.066	-0.28***	0.083
2019q4	-0.29***	0.042	-0.34***	0.051	-0.29***	0.063	-0.36***	0.072

Huber-White robust standard errors. (*) p-value < 0.1; (**) p-value < 0.05; (***) p-value < 0.01.

Dependent variable: expected average inflation 3-5 years ahead reported in the same quarter of information assignment.

The table reports the estimated coefficients on a dummy for having received information about current inflation obtained from period-by-period linear regressions of the dependent variable that also include sector dummies, area dummies, class size dummies and reported own price change over the last 12 months. Cols. (a) unweighted regression and (b) weighted regressions, sample excludes observations in the top and bottom 2 percent of the period-specific and information assignment-specific distribution of reported expected inflation; cols. (c) unweighted regression and (d) weighted regressions, sample includes all observations.

Table B.5: Effect of information assignment on expected own price change 12 months ahead.

	(a)		(b)		(c)		(d)	
Sample:	Trimmed				Untrimmed			
Weights:	No		Yes		No		Yes	
	Info	SE	Info	SE	Info	SE	Info	SE
2012q3	0.04	0.338	-0.42	0.486	0.01	0.332	-0.51	0.475
2012q4	-0.16	0.249	0.07	0.304	-0.17	0.246	0.07	0.294
2013q1	0.33	0.242	0.41	0.285	0.26	0.237	0.33	0.278
2013q2	-0.12	0.225	-0.25	0.287	-0.06	0.223	-0.17	0.285
2013q3	-0.07	0.272	-0.32	0.321	0.01	0.267	-0.24	0.312
2013q4	-0.05	0.290	-0.14	0.343	-0.01	0.295	-0.03	0.354
2014q1	-0.18	0.225	-0.24	0.285	-0.07	0.239	-0.17	0.290
2014q2	-0.23	0.229	-0.29	0.309	-0.28	0.243	-0.34	0.318
2014q3	0.46*	0.256	0.43	0.279	0.36	0.244	0.30	0.268
2014q4	0.24	0.232	0.16	0.284	0.22	0.227	0.11	0.277
2015q1	0.03	0.190	-0.12	0.242	0.02	0.189	-0.11	0.234
2015q2	-0.55	0.416	-0.43	0.476	-0.53	0.401	-0.41	0.456
2015q3	0.04	0.212	-0.07	0.240	0.07	0.209	-0.00	0.233
2015q4	-0.30	0.237	-0.25	0.315	-0.32	0.232	-0.31	0.306
2016q1	-0.10	0.210	0.04	0.242	-0.11	0.204	0.03	0.234
2016q2	-0.28	0.221	-0.37	0.251	-0.29	0.217	-0.36	0.245
2016q3	-0.25	0.174	-0.28	0.203	-0.25	0.173	-0.28	0.199
2016q4	0.05	0.225	0.10	0.273	-0.01	0.223	0.07	0.269
2017q1	-0.38*	0.205	-0.27	0.254	-0.30	0.210	-0.22	0.251
2017q2	-0.23	0.228	-0.07	0.235	-0.28	0.225	-0.13	0.241
2017q3	-0.01	0.220	-0.06	0.252	-0.06	0.211	-0.10	0.241
2017q4	-0.04	0.227	-0.10	0.225	-0.11	0.217	-0.18	0.218
2018q1	-0.27	0.308	-0.42	0.319	-0.33	0.317	-0.39	0.296
2018q2	0.19	0.223	0.54*	0.286	0.20	0.212	0.55**	0.273
2018q3	0.37**	0.178	0.49**	0.217	0.36**	0.173	0.48**	0.211
2018q4	0.07	0.249	0.17	0.269	0.06	0.241	0.14	0.260
2019q1	0.21	0.201	0.35*	0.209	0.22	0.195	0.36*	0.203
2019q2	-0.13	0.199	0.06	0.238	-0.08	0.195	0.07	0.230
2019q3	0.11	0.190	-0.03	0.206	0.10	0.180	-0.03	0.194
2019q4	-0.26	0.227	-0.24	0.261	-0.26	0.216	-0.24	0.248

Huber-White robust standard errors. (*) p-value < 0.1; (**) p-value < 0.05; (***) p-value < 0.01.

Dependent variable: expected own price change 12 months ahead reported in the same quarter of information assignment.

The table reports the estimated coefficients on a dummy for having received information about current inflation obtained from period-by-period linear regressions of the dependent variable that also include sector dummies, area dummies, class size dummies and reported own price change over the last 12 months. Cols. (a) unweighted regression and (b) weighted regressions, sample excludes observations in the top and bottom 2 percent of the period-specific and information assignment-specific distribution of reported expected inflation; cols. (c) unweighted regression and (d) weighted regressions, sample includes all observations.

Table B.6: Effect of information assignment on own price change 1 quarter after assignment.

	(a)		(b)		(c)		(d)	
Sample:	Trimmed				Untrimmed			
Weights:	No		Yes		No		Yes	
	Info	SE	Info	SE	Info	SE	Info	SE
2012q3	-0.29	0.292	-0.35	0.366	-0.32	0.287	-0.36	0.360
2012q4	-0.61**	0.278	-0.92**	0.396	-0.65**	0.271	-0.90**	0.387
2013q1	-0.11	0.295	0.03	0.325	-0.04	0.291	0.10	0.318
2013q2	0.39	0.357	0.57	0.482	0.26	0.358	0.44	0.480
2013q3	0.13	0.350	-0.20	0.398	0.13	0.341	-0.24	0.393
2013q4	0.56	0.357	0.66	0.401	0.28	0.375	0.21	0.463
2014q1	-0.03	0.337	-0.08	0.447	0.31	0.410	0.35	0.545
2014q2	-0.43	0.341	-0.46	0.426	-0.54	0.360	-0.61	0.442
2014q3	0.69*	0.372	0.46	0.469	0.56	0.378	0.30	0.477
2014q4	-0.33	0.309	-0.26	0.338	-0.34	0.299	-0.25	0.331
2015q1	-0.03	0.341	-0.22	0.399	-0.17	0.357	-0.31	0.407
2015q2	0.34	0.270	0.52*	0.310	0.16	0.280	0.31	0.315
2015q3	-0.37	0.299	-0.31	0.304	-0.39	0.291	-0.31	0.303
2015q4	0.29	0.244	0.29	0.258	0.15	0.308	0.12	0.322
2016q1	-0.55	0.400	-0.35	0.375	-0.52	0.387	-0.26	0.368
2016q2	-0.06	0.220	-0.01	0.261	-0.09	0.228	-0.07	0.270
2016q3	-0.26	0.284	-0.23	0.367	-0.37	0.279	-0.35	0.361
2016q4	-0.09	0.263	-0.13	0.299	-0.08	0.255	-0.08	0.286
2017q1	-0.58*	0.320	-0.59**	0.275	-0.58*	0.316	-0.62**	0.276
2017q2	-0.27	0.253	-0.25	0.286	-0.09	0.259	-0.09	0.290
2017q3	0.54**	0.259	0.35	0.300	0.49**	0.241	0.33	0.279
2017q4	-0.46*	0.270	-0.33	0.282	-0.56**	0.280	-0.34	0.283
2018q1	-0.05	0.299	-0.51	0.329	0.03	0.280	-0.42	0.312
2018q2	-0.13	0.237	-0.21	0.269	-0.09	0.226	-0.16	0.254
2018q3	0.25	0.328	0.02	0.327	0.15	0.324	-0.09	0.330
2018q4	-0.32	0.278	-0.67**	0.275	-0.25	0.275	-0.58**	0.275
2019q1	0.01	0.261	-0.09	0.308	0.03	0.252	-0.07	0.295
2019q2	-0.16	0.259	-0.38	0.302	-0.13	0.249	-0.33	0.289
2019q3	-0.05	0.196	-0.15	0.194	-0.05	0.187	-0.12	0.185
2019q4	0.00	0.000	0.00	0.000	0.00	0.000	0.00	0.000

Huber-White robust standard errors. (*) p-value < 0.1; (**) p-value < 0.05; (***) p-value < 0.01.

Dependent variable: own price change reported 1 quarter after information assignment.

The table reports the estimated coefficients on a dummy for having received information about current inflation obtained from period-by-period linear regressions of the dependent variable that also include sector dummies, area dummies, class size dummies and reported own price change over the last 12 months. Cols. (a) unweighted regression and (b) weighted regressions, sample excludes observations in the top and bottom 2 percent of the period-specific and information assignment-specific distribution of reported expected inflation; cols. (c) unweighted regression and (d) weighted regressions, sample includes all observations.

Table B.7: Effect of information assignment on own price change 2 quarters after assignment.

	(a)		(b)		(c)		(d)	
Sample:	Trimmed				Untrimmed			
Weights:	No		Yes		No		Yes	
	Info	SE	Info	SE	Info	SE	Info	SE
2012q3	0.35	0.292	0.23	0.469	0.34	0.287	0.23	0.456
2012q4	-0.27	0.282	-0.18	0.318	-0.21	0.286	-0.07	0.325
2013q1	0.05	0.375	0.24	0.468	0.16	0.374	0.29	0.458
2013q2	0.45	0.452	0.28	0.568	0.25	0.446	0.06	0.554
2013q3	0.44	0.372	0.47	0.494	0.46	0.371	0.46	0.485
2013q4	0.68**	0.336	0.86**	0.410	0.58*	0.340	0.63	0.429
2014q1	-0.66*	0.376	-0.38	0.457	-0.56	0.390	-0.32	0.473
2014q2	0.25	0.365	-0.08	0.421	0.32	0.361	-0.03	0.413
2014q3	0.36	0.319	0.34	0.369	0.34	0.312	0.30	0.364
2014q4	-0.69*	0.393	-0.77	0.509	-0.59	0.384	-0.64	0.497
2015q1	-0.06	0.287	-0.07	0.327	-0.05	0.288	-0.05	0.328
2015q2	-0.15	0.301	0.02	0.326	-0.25	0.299	-0.07	0.322
2015q3	-0.03	0.343	0.17	0.392	0.00	0.324	0.17	0.374
2015q4	-0.06	0.324	0.21	0.307	-0.35	0.407	-0.07	0.399
2016q1	-0.14	0.277	-0.02	0.298	-0.21	0.273	-0.08	0.297
2016q2	-0.26	0.322	-0.23	0.393	-0.34	0.313	-0.34	0.381
2016q3	0.13	0.263	0.09	0.361	0.01	0.260	-0.01	0.349
2016q4	-0.31	0.299	-0.59**	0.294	-0.55	0.354	-0.69**	0.299
2017q1	-0.23	0.320	-0.35	0.357	-0.18	0.307	-0.31	0.342
2017q2	-0.08	0.326	-0.19	0.388	0.06	0.310	-0.10	0.364
2017q3	-0.11	0.311	0.11	0.340	-0.07	0.296	0.17	0.319
2017q4	0.00	0.295	-0.44	0.309	-0.07	0.292	-0.49	0.306
2018q1	-0.37	0.271	-0.62*	0.329	-0.30	0.259	-0.55*	0.308
2018q2	0.25	0.332	0.25	0.381	0.17	0.325	0.12	0.378
2018q3	-0.32	0.280	-0.71**	0.279	-0.35	0.270	-0.74***	0.272
2018q4	0.00	0.286	-0.23	0.314	0.00	0.281	-0.26	0.309
2019q1	-0.33	0.272	-0.59*	0.324	-0.27	0.263	-0.52*	0.314
2019q2	-0.32	0.206	-0.42*	0.226	-0.25	0.197	-0.38*	0.218
2019q3								
2019q4								

Huber-White robust standard errors. (*) p-value < 0.1; (**) p-value < 0.05; (***) p-value < 0.01.

Dependent variable: own price change reported 2 quarters after information assignment.

The table reports the estimated coefficients on a dummy for having received information about current inflation obtained from period-by-period linear regressions of the dependent variable that also include sector dummies, area dummies, class size dummies and reported own price change over the last 12 months. Cols. (a) unweighted regression and (b) weighted regressions, sample excludes observations in the top and bottom 2 percent of the period-specific and information assignment-specific distribution of reported expected inflation; cols. (c) unweighted regression and (d) weighted regressions, sample includes all observations.

Table B.8: Effect of information assignment on own price change 4 quarters after assignment.

	(a)		(b)		(c)		(d)	
Sample:	Trimmed				Untrimmed			
Weights:	No		Yes		No		Yes	
	Info	SE	Info	SE	Info	SE	Info	SE
2012q3	-0.55	0.390	-0.91	0.620	-0.52	0.383	-0.88	0.611
2012q4	-0.19	0.342	-0.69	0.425	-0.20	0.339	-0.68*	0.415
2013q1	0.28	0.333	0.35	0.371	0.29	0.350	0.26	0.375
2013q2	0.46	0.372	0.31	0.497	0.41	0.365	0.27	0.484
2013q3	-0.37	0.390	-0.12	0.493	-0.34	0.394	-0.10	0.495
2013q4	0.58	0.411	0.52	0.454	0.50	0.402	0.39	0.448
2014q1	-0.42	0.323	-0.43	0.413	-0.31	0.338	-0.35	0.421
2014q2	-0.24	0.446	-0.48	0.516	-0.29	0.434	-0.57	0.500
2014q3	0.14	0.335	0.15	0.374	0.12	0.328	0.14	0.363
2014q4	-0.35	0.306	-0.18	0.350	-0.43	0.299	-0.26	0.348
2015q1	-0.07	0.256	0.08	0.283	-0.01	0.260	0.12	0.287
2015q2	-0.11	0.401	0.10	0.376	-0.12	0.393	0.09	0.368
2015q3	-0.21	0.262	-0.21	0.298	-0.12	0.257	-0.12	0.292
2015q4	-0.48	0.325	-0.54	0.379	-0.39	0.324	-0.43	0.383
2016q1	-0.08	0.283	-0.22	0.372	-0.11	0.291	-0.19	0.382
2016q2	-0.46	0.298	-0.70**	0.326	-0.65*	0.351	-0.75**	0.327
2016q3	-0.28	0.326	-0.48	0.355	-0.29	0.315	-0.46	0.347
2016q4	0.48	0.325	0.42	0.378	0.38	0.320	0.29	0.370
2017q1	-0.03	0.356	-0.17	0.399	-0.00	0.340	-0.12	0.376
2017q2	-0.06	0.377	-0.59	0.407	0.06	0.363	-0.45	0.386
2017q3	-0.42	0.285	-0.73**	0.351	-0.40	0.267	-0.63*	0.327
2017q4	0.21	0.310	-0.05	0.359	0.08	0.308	-0.13	0.354
2018q1	-0.50	0.309	-0.93***	0.309	-0.50*	0.295	-0.91***	0.294
2018q2	-0.13	0.289	-0.15	0.324	-0.28	0.291	-0.39	0.343
2018q3	-0.18	0.254	-0.40	0.288	-0.09	0.259	-0.25	0.307
2018q4	0.08	0.262	-0.17	0.283	0.07	0.256	-0.18	0.277
2019q1								
2019q2								
2019q3								
2019q4								

Huber-White robust standard errors. (*) p-value < 0.1; (**) p-value < 0.05; (***) p-value < 0.01.

Dependent variable: own price change reported 4 quarters after information assignment.

The table reports the estimated coefficients on a dummy for having received information about current inflation obtained from period-by-period linear regressions of the dependent variable that also include sector dummies, area dummies, class size dummies and reported own price change over the last 12 months. Cols. (a) unweighted regression and (b) weighted regressions, sample excludes observations in the top and bottom 2 percent of the period-specific and information assignment-specific distribution of reported expected inflation; cols. (c) unweighted regression and (d) weighted regressions, sample includes all observations.

Table B.9: Effect of information assignment on laboue demand 1 quarter after assignment.

	(a)		(b)		(c)		(d)	
Sample:	Trimmed				Untrimmed			
Weights:	No		Yes		No		Yes	
	Info	SE	Info	SE	Info	SE	Info	SE
2012q3	-0.02	0.034	0.00	0.025	-0.02	0.033	-0.00	0.025
2012q4	0.01	0.033	-0.01	0.021	0.01	0.031	-0.00	0.021
2013q1	0.01	0.027	-0.02	0.023	0.01	0.026	-0.01	0.022
2013q2	0.02	0.025	0.00	0.018	0.02	0.024	0.01	0.018
2013q3	0.00	0.026	-0.01	0.019	0.00	0.025	-0.01	0.018
2013q4	-0.01	0.028	-0.04*	0.021	-0.01	0.027	-0.04**	0.020
2014q1	0.02	0.030	-0.03	0.023	0.02	0.029	-0.02	0.022
2014q2	0.00	0.027	-0.01	0.019	0.00	0.026	-0.01	0.018
2014q3	0.02	0.026	0.01	0.019	0.01	0.025	0.01	0.019
2014q4	-0.02	0.026	-0.00	0.019	-0.02	0.025	0.00	0.019
2015q1	-0.00	0.025	-0.00	0.020	-0.00	0.024	-0.00	0.020
2015q2	0.02	0.024	0.01	0.020	0.02	0.023	0.01	0.019
2015q3	0.00	0.024	0.01	0.019	0.00	0.023	0.01	0.019
2015q4	-0.01	0.025	-0.01	0.018	-0.00	0.024	-0.01	0.018
2016q1	0.02	0.024	0.02	0.017	0.02	0.023	0.02	0.017
2016q2	-0.01	0.026	-0.01	0.020	-0.01	0.025	-0.01	0.020
2016q3	0.03	0.027	0.03	0.023	0.03	0.026	0.03	0.022
2016q4	0.01	0.027	-0.00	0.019	0.01	0.026	-0.01	0.018
2017q1	-0.02	0.033	-0.02	0.020	-0.02	0.031	-0.02	0.019
2017q2	0.06	0.043	0.02	0.022	0.06	0.039	0.03	0.021
2017q3	0.04	0.031	0.01	0.024	0.04	0.028	0.01	0.022
2017q4	0.04	0.030	0.01	0.021	0.04	0.028	0.01	0.021
2018q1	0.04	0.034	0.02	0.022	0.05	0.032	0.02	0.021
2018q2	0.02	0.033	0.01	0.022	0.01	0.032	-0.00	0.021
2018q3	0.04	0.033	0.03	0.022	0.04	0.032	0.03	0.021
2018q4	0.04	0.031	0.04*	0.023	0.04	0.030	0.04*	0.022
2019q1	0.03	0.031	0.01	0.024	0.03	0.030	0.01	0.023
2019q2	0.03	0.031	0.04**	0.021	0.03	0.030	0.03	0.021
2019q3	0.01	0.032	0.03	0.022	0.02	0.030	0.03	0.021
2019q4								

Huber-White robust standard errors. (*) p-value < 0.1; (**) p-value < 0.05; (***) p-value < 0.01.

Dependent variable: labour demand 1 quarter after information assignment.

The table reports the estimated coefficients on a dummy for having received information about current inflation obtained from period-by-period linear regressions of the dependent variable that also include sector dummies, area dummies, class size dummies and reported own price change over the last 12 months. Cols. (a) unweighted regression and (b) weighted regressions, sample excludes observations in the top and bottom 2 percent of the period-specific and information assignment-specific distribution of reported expected inflation; cols. (c) unweighted regression and (d) weighted regressions, sample includes all observations.

Table B.10: Effect of information assignment on labour demand 2 quarters after assignment.

	(a)		(b)		(c)		(d)	
Sample:	Trimmed				Untrimmed			
Weights:	No		Yes		No		Yes	
	Info	SE	Info	SE	Info	SE	Info	SE
2012q3	-0.02	0.044	-0.01	0.026	-0.03	0.043	-0.01	0.025
2012q4	0.02	0.035	-0.01	0.026	0.01	0.034	-0.01	0.027
2013q1	0.01	0.027	-0.01	0.021	0.01	0.026	-0.01	0.021
2013q2	0.01	0.027	-0.00	0.019	0.01	0.026	0.00	0.019
2013q3	0.01	0.028	-0.02	0.021	0.01	0.027	-0.01	0.020
2013q4	-0.03	0.029	-0.06**	0.025	-0.03	0.028	-0.06**	0.024
2014q1	0.00	0.027	-0.02	0.023	0.01	0.027	-0.02	0.022
2014q2	0.02	0.028	0.00	0.021	0.02	0.027	0.00	0.020
2014q3	0.00	0.027	-0.01	0.020	0.00	0.026	-0.00	0.020
2014q4	-0.00	0.028	-0.01	0.022	-0.01	0.027	-0.01	0.022
2015q1	0.00	0.025	0.01	0.021	0.00	0.024	0.01	0.020
2015q2	-0.00	0.026	0.00	0.022	-0.00	0.025	0.00	0.021
2015q3	-0.00	0.025	0.00	0.020	0.00	0.024	0.01	0.020
2015q4	-0.01	0.026	-0.01	0.019	-0.01	0.026	-0.01	0.019
2016q1	0.01	0.025	0.01	0.018	0.01	0.024	0.00	0.018
2016q2	0.02	0.026	0.01	0.021	0.03	0.026	0.02	0.021
2016q3	0.03	0.029	0.03	0.023	0.03	0.029	0.03	0.023
2016q4	0.01	0.032	-0.01	0.021	0.01	0.031	-0.00	0.021
2017q1	-0.01	0.035	0.00	0.020	-0.01	0.034	-0.01	0.019
2017q2	0.05*	0.028	0.03	0.021	0.05*	0.027	0.03*	0.020
2017q3	0.03	0.034	0.01	0.025	0.03	0.032	0.01	0.024
2017q4	0.06*	0.032	0.03	0.022	0.06*	0.030	0.02	0.021
2018q1	0.04	0.034	0.01	0.022	0.04	0.032	0.01	0.021
2018q2	0.04	0.035	0.03	0.025	0.03	0.034	0.02	0.024
2018q3	0.05	0.033	0.04*	0.024	0.05*	0.032	0.05**	0.024
2018q4	0.04	0.033	0.03	0.026	0.04	0.032	0.03	0.025
2019q1	-0.00	0.031	-0.00	0.025	-0.00	0.031	-0.00	0.024
2019q2	0.01	0.033	0.04	0.023	0.01	0.032	0.02	0.022
2019q3								
2019q4								

Huber-White robust standard errors. (*) p-value < 0.1; (**) p-value < 0.05; (***) p-value < 0.01.

Dependent variable: labour demand 2 quarters after information assignment.

The table reports the estimated coefficients on a dummy for having received information about current inflation obtained from period-by-period linear regressions of the dependent variable that also include sector dummies, area dummies, class size dummies and reported own price change over the last 12 months. Cols. (a) unweighted regression and (b) weighted regressions, sample excludes observations in the top and bottom 2 percent of the period-specific and information assignment-specific distribution of reported expected inflation; cols. (c) unweighted regression and (d) weighted regressions, sample includes all observations.

Table B.11: Effect of information assignment on labour demand 3 quarters after assignment.

	(a)		(b)		(c)		(d)	
Sample:	Trimmed				Untrimmed			
Weights:	No		Yes		No		Yes	
	Info	SE	Info	SE	Info	SE	Info	SE
2012q3	-0.03	0.040	-0.03	0.026	-0.03	0.038	-0.03	0.025
2012q4	0.01	0.034	-0.02	0.023	0.01	0.033	-0.01	0.023
2013q1	-0.00	0.028	-0.03	0.022	-0.01	0.027	-0.03	0.021
2013q2	0.01	0.029	-0.02	0.022	0.01	0.028	-0.02	0.021
2013q3	-0.00	0.031	-0.04	0.027	0.00	0.029	-0.03	0.026
2013q4	-0.02	0.031	-0.04*	0.026	-0.03	0.030	-0.05*	0.026
2014q1	0.01	0.029	-0.01	0.025	0.00	0.028	-0.01	0.024
2014q2	-0.01	0.026	-0.02	0.021	-0.01	0.025	-0.02	0.020
2014q3	0.00	0.028	-0.01	0.022	0.01	0.027	-0.00	0.021
2014q4	0.01	0.027	0.02	0.022	0.01	0.026	0.02	0.022
2015q1	-0.01	0.026	0.00	0.021	-0.01	0.026	0.00	0.020
2015q2	0.01	0.026	0.00	0.021	0.01	0.025	-0.00	0.021
2015q3	0.00	0.025	-0.00	0.021	0.01	0.024	0.00	0.020
2015q4	-0.03	0.028	-0.03	0.023	-0.02	0.027	-0.02	0.022
2016q1	0.03	0.025	0.04*	0.019	0.04	0.024	0.03*	0.018
2016q2	0.02	0.028	0.01	0.021	0.03	0.028	0.01	0.021
2016q3	0.02	0.032	0.01	0.021	0.02	0.031	0.02	0.021
2016q4	0.01	0.035	0.01	0.021	0.00	0.034	0.01	0.021
2017q1	-0.02	0.033	-0.03	0.022	-0.02	0.031	-0.03	0.021
2017q2	0.03	0.032	0.03	0.021	0.04	0.030	0.04*	0.020
2017q3	0.04	0.035	0.02	0.026	0.04	0.033	0.02	0.025
2017q4	0.04	0.031	0.02	0.024	0.04	0.030	0.02	0.023
2018q1	0.03	0.036	0.00	0.025	0.03	0.033	0.01	0.024
2018q2	0.06	0.037	0.04	0.033	0.06	0.035	0.04	0.032
2018q3	0.04	0.034	0.04	0.027	0.04	0.032	0.03	0.026
2018q4	0.01	0.032	0.01	0.026	0.01	0.031	0.01	0.026
2019q1	-0.00	0.035	-0.01	0.025	-0.01	0.034	-0.01	0.025
2019q2								
2019q3								
2019q4								

Huber-White robust standard errors. (*) p-value < 0.1; (**) p-value < 0.05; (***) p-value < 0.01.

Dependent variable: labour demand 3 quarters after information assignment.

The table reports the estimated coefficients on a dummy for having received information about current inflation obtained from period-by-period linear regressions of the dependent variable that also include sector dummies, area dummies, class size dummies and reported own price change over the last 12 months. Cols. (a) unweighted regression and (b) weighted regressions, sample excludes observations in the top and bottom 2 percent of the period-specific and information assignment-specific distribution of reported expected inflation; cols. (c) unweighted regression and (d) weighted regressions, sample includes all observations.

Table B.12: Effect of information assignment on labour demand 4 quarters after assignment.

	(a)		(b)		(c)		(d)	
Sample:	Trimmed				Untrimmed			
Weights:	No		Yes		No		Yes	
	Info	SE	Info	SE	Info	SE	Info	SE
2012q3	-0.04	0.045	-0.03	0.028	-0.05	0.043	-0.04	0.027
2012q4	-0.01	0.032	-0.05*	0.023	-0.01	0.031	-0.04*	0.023
2013q1	0.00	0.032	-0.02	0.025	0.00	0.031	-0.02	0.024
2013q2	0.02	0.035	-0.03	0.026	0.02	0.034	-0.03	0.026
2013q3	-0.00	0.031	-0.02	0.028	0.00	0.029	-0.01	0.027
2013q4	-0.03	0.033	-0.05	0.028	-0.02	0.032	-0.05*	0.027
2014q1	-0.01	0.030	-0.02	0.029	-0.02	0.029	-0.03	0.028
2014q2	0.00	0.028	-0.02	0.023	0.00	0.027	-0.02	0.022
2014q3	0.03	0.028	0.02	0.022	0.03	0.027	0.03	0.021
2014q4	-0.01	0.028	0.01	0.023	-0.01	0.028	0.01	0.022
2015q1	-0.00	0.025	0.00	0.021	-0.01	0.025	-0.00	0.020
2015q2	0.01	0.028	-0.00	0.023	0.02	0.027	-0.00	0.022
2015q3	-0.01	0.025	0.01	0.021	-0.00	0.024	0.01	0.020
2015q4	0.00	0.028	0.00	0.024	0.00	0.027	0.00	0.023
2016q1	0.01	0.027	0.01	0.019	0.01	0.026	0.01	0.019
2016q2	-0.01	0.033	-0.02	0.026	-0.00	0.032	-0.02	0.025
2016q3	0.01	0.034	0.03	0.020	0.01	0.033	0.03	0.020
2016q4	-0.00	0.032	-0.01	0.023	-0.01	0.031	-0.01	0.023
2017q1	-0.00	0.034	-0.01	0.021	-0.00	0.032	-0.01	0.020
2017q2	0.04	0.033	0.03	0.022	0.04	0.031	0.03	0.020
2017q3	0.02	0.034	0.01	0.025	0.02	0.032	0.02	0.024
2017q4	0.08**	0.035	0.03	0.028	0.08**	0.033	0.03	0.027
2018q1	0.06*	0.036	0.03	0.031	0.06*	0.034	0.03	0.029
2018q2	0.04	0.035	0.03	0.033	0.03	0.034	0.03	0.032
2018q3	0.01	0.034	0.02	0.027	0.00	0.032	0.01	0.026
2018q4	0.00	0.034	0.01	0.028	0.00	0.034	0.01	0.027
2019q1								
2019q2								
2019q3								
2019q4								

Huber-White robust standard errors. (*) p-value < 0.1; (**) p-value < 0.05; (***) p-value < 0.01.

Dependent variable: labour demand 4 quarters after information assignment.

The table reports the estimated coefficients on a dummy for having received information about current inflation obtained from period-by-period linear regressions of the dependent variable that also include sector dummies, area dummies, class size dummies and reported own price change over the last 12 months. Cols. (a) unweighted regression and (b) weighted regressions, sample excludes observations in the top and bottom 2 percent of the period-specific and information assignment-specific distribution of reported expected inflation; cols. (c) unweighted regression and (d) weighted regressions, sample includes all observations.

Appendix C Bad controls

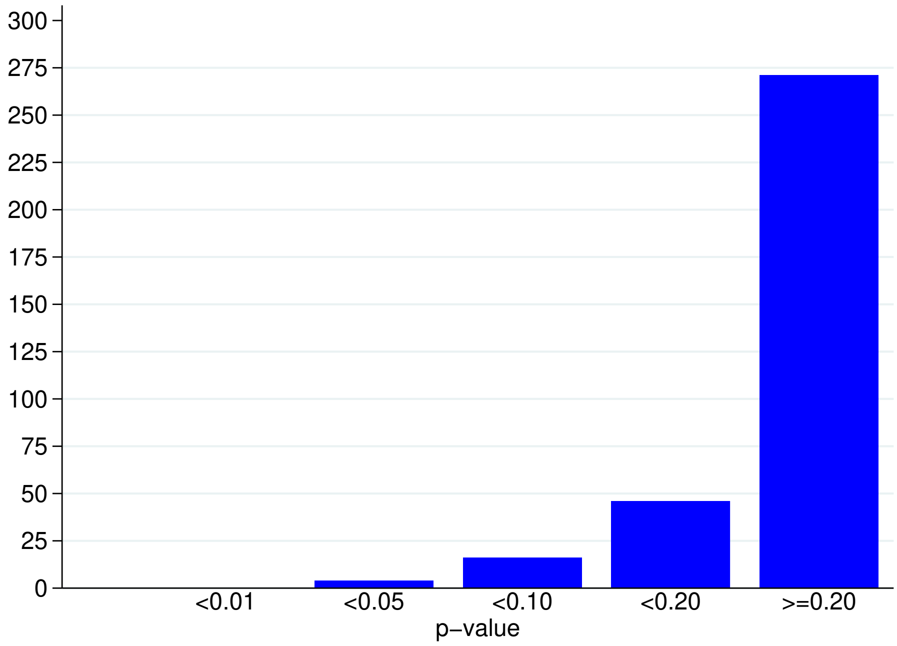
The main OLS reduced form specification in the paper is:

$$y_{it+k} = a + b_t I_{it} + d_t X_{it} + e_{it} \tag{C.1}$$

Persistence of the random assignment implies that $I_{it} = I_i \quad \forall t$ in which i participates in the survey. Because the control set X_{it} includes lagged or contemporaneous values of some outcomes of interest (specifically, own past price changes and dummies for current firm size), it is possible that estimates of b_t are biased by the fact that these variables have been affected by (the persistent) assignment status in the past.

To address this possibility, for each dependent variable and quarter I test that estimates of b_t obtained from OLS estimations of equation (C.1) are equal to those obtained from a specification in which the coefficients of own past price change and of firm size dummies are constrained to be zero. The exercise generates 337 tests and associated p-values. Figure (C.1) displays their distribution. No test rejects the null of equality at 1 percent, only 4 do at 5 percent and only 16 at 10 percent; 271 test have a p-value above 20 percent. Besides, contrary to what could be expected if persistence of the assignment biased coefficient estimates due to the endogeneity of some controls, of the 20 tests that reject the null with at most 10 percent probability, 10 refer to coefficient estimates for the period 2012:3 to 2013:3, that is the initial quarters of the RCT rather that later ones when the cumulated effect on lagged endogenous variables would have introduced a larger bias.

Figure C.1: Equality of the effects of information exposure across specifications



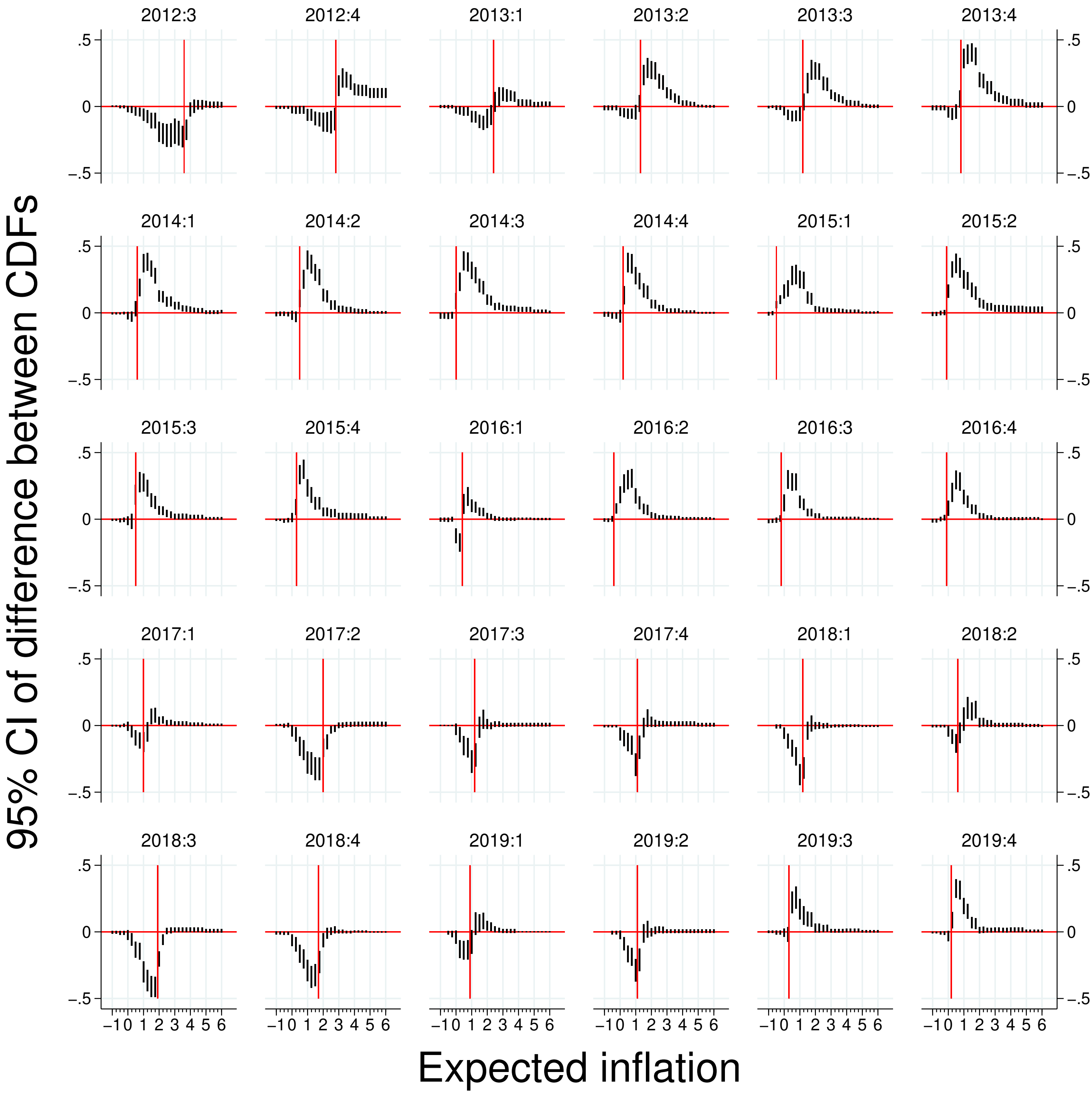
Source: Own elaborations of Bank of Italy Survey of Inflation and Growth Expectations.

Appendix D No crossing

In the case of multivalued treatments a necessary condition for the monotonicity assumption to be satisfied is that the cumulative distribution function (CDF) of the treatment variable $F\pi$ conditional on being presented with the signal, $I = 1$, and the CDF of $F\pi$ conditional on not being presented with it, $I = 0$, should not cross.

Following Angrist and Imbens (1995), in figure (D.1) I plot the 95 percent pointwise confidence intervals of the differences between the CDFs of expected inflation of informed and uninformed firms in each quarter, along with a vertical bar in correspondence of the value of inflation presented to informed firms. Specifically, I construct the confidence intervals as follows. I consider a finite set of values of expected inflation $e \in \{e_1, e_2, \cdots, e_N\}$, define $y_i^k = I(F_i\pi \leq e_k)$ and estimate, for each quarter and for each value e_k, $y_i^k = a + b_k I_i + \epsilon_i$ using sample weights and Huber-White robust standard errors. The figure thus displays the set of quarter-specific 95 percent confidence intervals of $\hat{b}_k$ for $k \in \{1, \cdots, N\}$. In several periods, statistically significant negative and positive differences between the two CDFs coexist thus leading to a rejection of the monotonicity assumption.

Figure D.1: Informed-uninformed difference in inflation expectations CDF.



Source: Own elaborations of Bank of Italy Survey of Inflation and Growth Expectations.

Appendix E IVQR results

IVQR models for deciles 1 to 9 are estimated for each quarter. Dependent variables are expected own price change over the next year, the annual price change reported 1, 2, and 4 quarters after assignment and (log) employment 1, 2, 3, and 4 quarters after assignment. For all models, the conditioning set includes expected inflation one year ahead, the change in own price over the past 12 months, and dummies for firm size, area and sector. Expected inflation is instrumented with the assignment status dummy.

Tables (E.1) and (E.2) report, for each quarter and dependent variable, the deciles at which IVQR estimates of the coefficient on expected inflation is statistically different from zero with 5 percent probability.

Table E.1: IVQR: significant effects of expected inflation on own prices.

Dep. var.	$E_t \Delta p_{t+4}$	Δp_{t+1}	Δp_{t+2}	Δp_{t+4}
2012q3			8;9	
2012q4				
2013q1				1;2;3
2013q2				
2013q3	1			
2013q4			9	
2014q1		7;8		
2014q2				
2014q3		9	9	8
2014q4	8;9			
2015q1	1			
2015q2		9		
2015q3				
2015q4	4;5;6			
2016q1				8
2016q2		2		
2016q3				
2016q4				
2017q1	1	9	7	
2017q2				
2017q3		2		
2017q4				
2018q1				
2018q2				
2018q3	7;8;9			
2018q4				
2019q1				na
2019q2				na
2019q3			na	na
2019q4		na	na	na

The table reports, for each dependent variable, the deciles at which coefficients on one-year-ahead expected inflation from an IVQR estimate are statistically different from zero at 5 percent. Empty cells mean that coefficients at all deciles do not reach the 5 percent threshold of statitical significance. (na) no observations. The IVQR regression includes also own price change over the previous year, and dummies for firm size, area and sector.

Table E.2: IVQR: significant effects of expected inflation of labour demand.

Dep. var.	L_{t+1}	L_{t+2}	L_{t+3}	L_{t+4}
2012q3		3		
2012q4				6
2013q1				
2013q2				
2013q3				
2013q4				
2014q1				1;9
2014q2				1
2014q3				
2014q4				
2015q1				
2015q2				
2015q3				
2015q4				
2016q1			9	
2016q2		9	9	
2016q3				
2016q4				
2017q1	9			
2017q2	3			
2017q3				
2017q4				7
2018q1				
2018q2				
2018q3				
2018q4	7			
2019q1				na
2019q2	9		na	na
2019q3		na	na	na
2019q4	na	na	na	na

The table reports, for each dependent variable, the deciles at which coefficients on one-year-ahead expected inflation from an IVQR estimate are statistically different from zero at 5 percent. Empty cells mean that coefficients at all deciles do not reach the 5 percent threshold of statitical significance. (na) no observations. The IVQR regression includes also own price change over the previous year, and dummies for firm size, area and sector.

Appendix F Derivation of CGR main estimated coefficients

Consider Coibion et al. (2020b)'s first stage equation[34]:

$$F_{it}\pi = \rho + \theta T_{it} + \epsilon_{it} \tag{F.1}$$

where $T_{it} = \pi_t * I_{it}$ and $I_{it} \in \{0, 1\}$ is randomly assigned. Recall also that $\forall t \quad F^0_{it}\pi = \gamma\Pi^0_{it} + u_{it}$ and $F^1_{it}\pi = \gamma\Pi^1_{it} + u_{it} = \gamma\omega\pi_t + \gamma(1-\omega)\Pi^0_{it}) + u_{it}$ where with respect to the discussion in the text I have made explicit the time dimension in describing counterfactual expectations.

Comparing the expected values of equation (F.1) conditional on time t and assignment status $I_{it} = 0$ with the expected value of the corresponding counterfactual expected inflation reveals that $E(F^0_{it}\pi|t) = \gamma E(\Pi^0_{it}|t)$ but $E(F_{it}\pi|t, I_{it} = 0) = \rho$, so that equation (F.1) implicitly imposes that absent the signal the average assessment of current inflation, Π^0_{it} and therefore expected inflation, $F^0_{it}\pi$, is constant over time. This is clearly in contrast with the descriptive evidence that inflation expectations of uninformed firms move over time. Furthermore, comparing the expression for expected inflation when exposed to the signal, $F^1_{it}\pi = \gamma\omega\pi_t + \gamma(1-\omega)\Pi^0_{it} + u_{it}$ to its empirical counterpart given by equation (F.1), $F_{it}\pi = \rho + \theta\pi_t + \epsilon_{it}$, reveals that, since $E(\pi_t, \Pi^0_{it})$ is unlikely to be nil, the assumption $E(T_{it}, \epsilon_{it}) = 0$ required to consistently estimate θ from (F.1) is unlikely to be satisfied. Indeed, the descriptive evidence shows that not only the average inflation expectations of uninformed firms move over time, but also that they move together with current inflation, that is with the signal π_t. Clearly, imposing that $E(F^0_{it}\pi|t)$ or, equivalently, that $E(\Pi^0_{it}|t)$ is constant over time amounts to assuming away the potential correlation between the signal and the residual in equation (F.1).

Figure (F.1) offers a visual representation of the above argument. In the left-hand panel I display the cloud of data points fitted by the regression estimated by CGR with the specification in equation (F.1): the y-axis reports the dependent variable, that is inflation expectations of informed firms (solid circles) and of uninformed ones (hollow squares) and the x-axis the value of the CGR treatment variable T_{it}, that is the inflation rate presented to the randomly informed firms and zero for the non informed ones[35]. The identifying variation underlying estimates of θ stems mostly from the positive correlation over time between current inflation and expected inflation of firms presented with current inflation rates; this would obviously be the case also if uninformed firms were imputed a different arbitrary constant assessment of current inflation. In the right-hand panel I plot the expectations of both informed and uninformed firms against current inflation. Unsurprisingly, the expectations of uninformed firms too are positively correlated with current inflation, most likely reflecting the fact that they also exploit some information about recent developments to form their expectations. This, however, implies

[34]For expositional ease, I consider a simplified version on their specification that only retains the essential elements and abstract from exogenous variables (firm characteristics or seasonal dummies).

[35]For the sake of simplicity, the figure reports only average one-year inflation expectations computed by quarter and information status.

that the source of identifying variation in equation (F.1) cannot be claimed to be exogenously generated by the RCT.

More formally, consider estimating equation (F.1) by OLS so that

$$\hat{\theta} = \frac{cov(F_{it}\pi, T_{it})}{V(T_{it})}$$

Both the numerator and the denominator can be decomposed in the within- and between-group components, where the groups are given by informed ($I_{it} = 1$) and uninformed ($I_{it} = 0$) firms.

$$\begin{aligned} cov(F_{it}\pi, T_{it}) = {} & P(I_{it} = 1)cov(F_{it}\pi, T_{it}|I_{it} = 1)+ \\ & + P(I_{it} = 0)cov(F_{it}\pi, T_{it}|I_{it} = 0)+ \\ & + P(I_{it} = 1)(E(F_{it}\pi|I_{it} = 1) - E(F_{it}\pi))(E(T_{it}|I_{it} = 1) - E(T_{it}))+ \\ & + P(I_{it} = 0)(E(F_{it}\pi|I_{it} = 0) - E(F_{it}\pi))(E(T_{it}|I_{it} = 0) - E(T_{it})) \end{aligned} \tag{F.2}$$

$$\begin{aligned} V(T_{it}) = {} & P(I_{it} = 1)V(T_{it}|I_{it} = 1) + P(I_{it} = 0)V(T_{it}|I_{it} = 0)+ \\ & + P(I_{it} = 1)(E(T_{it}|I_{it} = 1) - E(T_{it}))^2 + P(I_{it} = 0)(E(T_{it}|I_{it} = 0) - E(T_{it}))^2 \end{aligned} \tag{F.3}$$

By combining the two expressions above it is easy to obtain:

$$\begin{aligned} \hat{\theta} = {} & \frac{cov(F_{it}\pi, T_{it}|I_{it} = 1)}{V(T_{it}|I_{it} = 1)} \frac{P(I_{it} = 1)V(T_{it}|I_{it} = 1)}{V(T_{it})} + \\ & + \frac{cov(F_{it}\pi, T_{it}|I_{it} = 0)}{V(T_{it}|I_{it} = 0)} \frac{P(I_{it} = 0)V(T_{it}|I_{it} = 0)}{V(T_{it})} + \\ & + \frac{E(F_{it}\pi|I_{it} = 1) - E(F_{it}\pi|I_{it} = 0)}{E(T_{it}|I_{it} = 1) - E(T_{it}|I_{it} = 0)} \frac{P(I_{it} = 1)P(I_{it} = 0)(E(T_{it}|I_{it} = 1) - E(T_{it}|I_{it} = 0))^2}{V(T_{it})} \end{aligned} \tag{F.4}$$

where I have used $E(X) = P(I = 1)E(X|I = 1) + (1 - P(I = 1))E(X|I = 0)$. Equation (F.4) expresses the coefficient θ resulting from an OLS estimation of equation (F.1) on $\{F_{it}\pi, T_{it}\}_{i=1,\dots,N;t=1,\dots,Q}$ as a weighted average. The first two terms are the OLS coefficients obtained from separate estimations of equation (F.1) on the subsets of observations $I_{it} = 1$ and $I_{it} = 0$; the third term is the ratio of the difference across the two groups of the means over (i, t) of the dependent variable and of the explanatory variable T_{it}. The weights are the shares of the total variance of the explanatory variable T_{it} due to variation within each group I and to variation between the two groups.

In principle, the first two terms reflect variation across firms and over time within each group; the third term reflects only variation across groups. However, since $T_{it} = \pi_t I_{it}$, the within group variation stems only from variation over time for informed firms ($I_{it} = 1$) and is zero for the uninformed group ($I_{it} = 0$). Therefore, $E(T_{it}|I_{it} = 0) = 0$ and $cov(F_{it}\pi, T_{it}|I_{it} = 0) = 0$;

moreover, $E(T_{it}|I_{it} = 1) = \bar{\pi}^*$ that is the mean over time of observed inflation, π_t. Also, because within informed firms T_{it} varies only over time the first term in equation (F.4):

$$cov(F_{it}\pi, T_{it}|I_{it} = 1) = cov(\bar{F}_t^1\pi, \pi_t) \qquad \bar{F}_t^1\pi = E(F_j^i\pi|I_j^i = 1, j = t) \tag{F.5}$$

thus reflecting only the covariance over time between observed inflation π_t and average expectations of informed firms in the corresponding period.

Bringing all these considerations together simplifies expression (F.4) into:

$$\begin{aligned}\hat{\theta}_{CGR} &= \frac{cov(\bar{F}_t^1\pi, \pi_t)}{V(\pi_t|I_{it} = 1)}\Sigma_T^1 + \left(\frac{E(F_{it}\pi|I_{it} = 1) - E(F_{it}\pi|I_{it} = 0)}{\bar{\pi}^*}\right)\left(1 - \Sigma_T^1\right) \\ &= \theta_T^1\Sigma_T^1 + \frac{\Delta^F}{\bar{\pi}_t^*}\left(1 - \Sigma_T^1\right)\end{aligned} \tag{F.6}$$

where $\Sigma_T^1 = \frac{V(\pi_t|I_{it}=1)P(I_{it}=1)}{V(T_{it})}$ is the share of the overall variance of the treatment T_{it} due to variation within the group of firms randomly exposed to information, which by construction stems exclusively from variation over time.

The estimate $\hat{\theta}_{CGR}$ is thus a weighted average of two terms. The first one (θ_T^1) is the result one would obtain by estimating (F.1) only on the subsample of firms exposed to the information treatment, thus identified only out of the covariance over time between (mean) expectations of informed firms and current inflation and obviously subject to all criticisms that in the first place induced to look for exogenous variation in perceived inflation to estimate the causal effect of interest.

The second one ($\Delta^F/\bar{\pi}^*$) resembles a causal object in that it relates the difference in average expectations across randomly determined assignment status ($\Delta^F = E(F_{it}\pi|I_i = 1) - E(F_{it}\pi|I_i = 0)$) to the mean observed inflation, $\bar{\pi}^*$, that CGR implicitly assume to be the average effect of being exposed to the signal on the mean perceived current inflation ($E(T_{it}|I_i = 1) - E(T_{it}|I_i = 0) = \bar{\pi}^*$). Yet, as shown above in equation (2), the true effect of being exposed to the signal on the average assessment of current inflation is $E(\Pi_{it}^1) - E(\Pi_{it}^0) = \omega(\bar{\pi}^* - E(\Pi_{it}^0))$, so that the quantity $\Delta^F/\bar{\pi}^*$ has no causal interpretation either.

In table (F.1) I compute the elements contributing to $\hat{\theta}_{CGR}$ according to equation (F.6); I focus only on the one-year expected inflation and on estimates obtained on the entire sample (2012:3-2019:1) and for those obtained on the mostly ELB period only (2014:1-2019:1). For simplicity, my calculations are based on a regression that does not include the interaction of 5 sector dummies and 4 quarter dummies used in CGR to control for seasonality; the randomised nature of the information provision guarantees that these controls are inessential. Rows (a) and (b) of the table compare the coefficients obtained with and without these additional controls. Combining elements in rows (c)-(l) according to equation (F.6) yields the estimate in row (m), which coincides with the one obtained from direct estimation of equation (F.1) reported in row (b). The table shows that estimates supporting causal statements on the effects of information on expectations in CGR stem exclusively from the covariation over time between inflation rates presented to informed firms and their (mean) future expected inflation (θ_T^1), that in both cases enters the final estimate with a weight (Σ_T^1) larger than 0.8. Comparisons of expectations across randomly assigned treatment groups (Δ^F), on the other hand, play a definitely marginal role: the latter term in (F.6) is indeed negative, reflecting the fact that over both periods average inflation expectations of informed firms are *lower* than those of uninformed ones, and largely by the same amount irrespective of the ELB.

Incidentally, note that this is at odds with the implications of CGR estimates. Since $E(F_{it}\pi|I_i = 1, t) - E(F_{it}\pi|I_i = 0, t) = \hat{\theta}_{CGR}\pi_t^*$, CGR results imply that (a) on average, over the 2012:3-2019:1 period the inflation expectations of firms presented with the current information are *higher* than those of firms in the uninformed group and (b) the sign of the difference depends on whether inflation is positive or negative, so that in quarters when firms were presented with negative inflation rates (early 2015 and late 2016) average expectations of informed firms are *lower* than those of non informed ones while they are *higher* in the other quarters when inflation was positive, a feature not borne out by the data. The fact that expectations of informed firms are on average below those of uninformed ones is only tangentially mentioned in CGR but the apparent inconsistency with results in their table (2) is not discussed.

This misinterpretation carries over to the 2SLS presented in CGR. Intuitively, the 2SLS can be expressed as the ratio of the reduced form coefficient obtained from a regression of the outcome of interest Y_{it} on the treatment variable T_{it} and the first stage coefficient just discussed[36]. Because the reduced form estimate rests on the same sources of identification as the first stage, an expression analogous to (F.6) can be easily obtained for the numerator of the reduced form coefficient. The ratio of interest can then be shown to be:

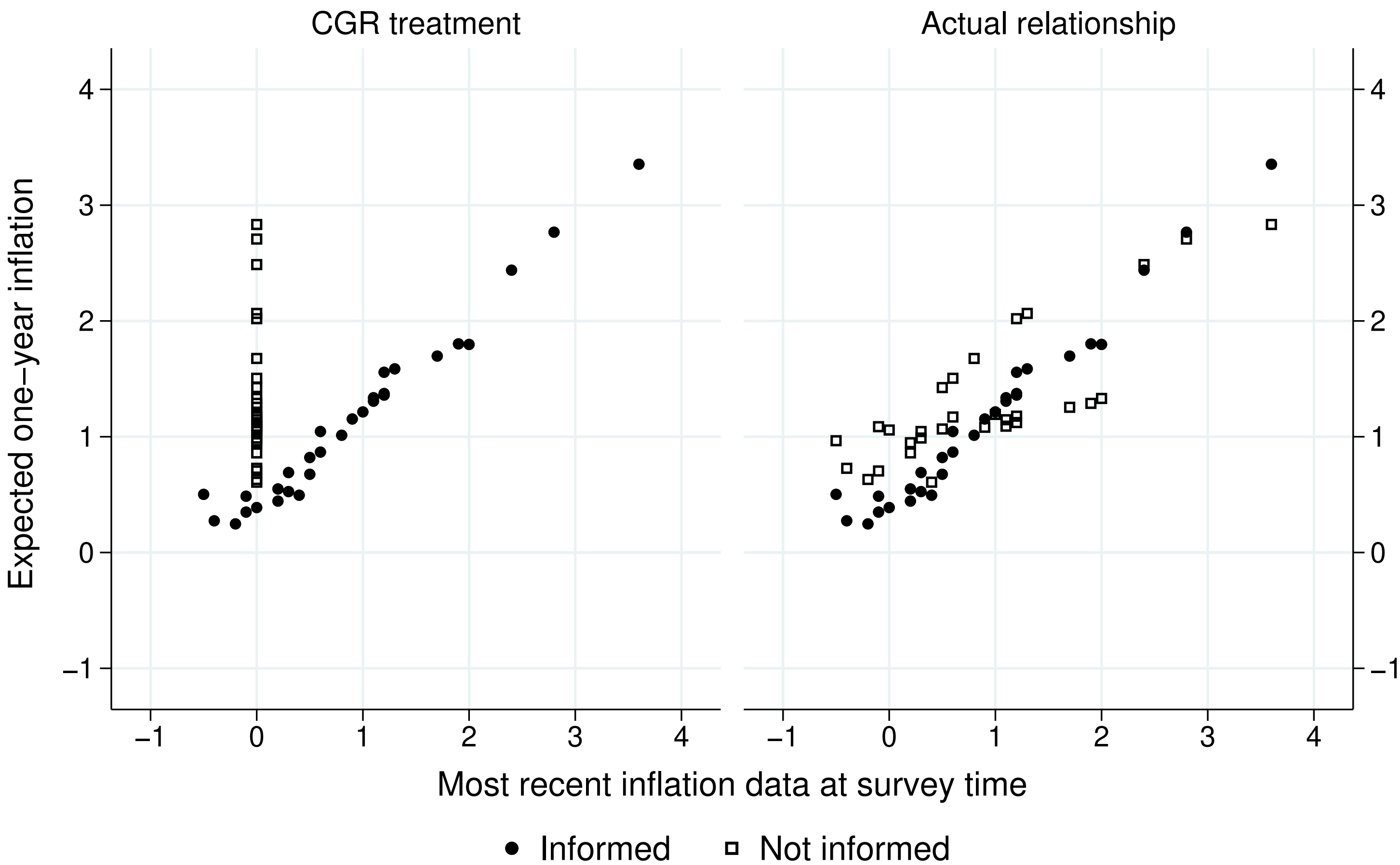
$$\begin{aligned}\hat{\gamma}_{CGR} &= \frac{\lambda_T^1\Sigma_T^1 + \left(\Delta^Y/\bar{\pi}^*\right)\left(1-\Sigma_T^1\right)}{\theta_T^1\Sigma_T^1 + \left(\Delta^F/\bar{\pi}^*\right)\left(1-\Sigma_T^1\right)} \\ &= \frac{\lambda_T^1}{\theta_T^1}\frac{\theta_T^1\Sigma_T^1}{\hat{\theta}_{CGR}} + \frac{\Delta^Y}{\Delta^F}\left(1-\frac{\theta_T^1\Sigma_T^1}{\hat{\theta}_{CGR}}\right)\end{aligned} \tag{F.7}$$

The 2SLS estimated coefficient is therefore the weighted average of two terms, with weights essentially reflecting the relevance of time variation in identifying the first stage coefficient θ from equation (F.1). The first term, $\frac{\lambda_T^1}{\theta_T^1}$, is the ratio between the reduced form and the first stage coefficients when both equations are estimated only on the subset of firms presented with information about current inflation, thus again identified only out of time variation. The second one, $\frac{\Delta^Y}{\Delta^F}$, is the ratio between the difference in average outcomes across information groups and the corresponding difference in average inflation expectations computed on the entire sample period, thus again unrelated to the specific piece of information provided in each period. Notice

[36] I abstract from details of the empirical specification in CGR that do not affect the sources of identifying variation. Specifically, they consider the effect of *previous* period expectations on *current* outcomes and add controls for exogenous firm characteristics as well as for a set of firm-level potentially endogenous variables (decisions, expectations, assessments) elicited as of time $t-2$. The choices about the timing of the main explanatory variable $F_{t-1}^i\pi$ and of the controls are rightly motivated with the necessity of controlling as much as possible for broader firm's expectations so as to be able to "interpret the coefficient on $F_{t-1}^i\pi$ as the response of the outcome to a surprise movement in inflation expectations".

also that in this specific application the weight on the first term, $\frac{\theta_T^1 \Sigma_T^1}{\hat{\theta}_{CGR}}$, is larger than one. This can be easily seen in equation (F.6) recalling that over the relevant sample $\Delta^F < 0$ that is expectations of informed firms are on average below those of uninformed ones. This also means that in expression (F.7) the only term suitable of some causal interpretation, $\frac{\Delta^Y}{\Delta^F}$, attracts a negative weight.

Figure F.1: Graphical representation of CGR first stage.



Source: Own elaborations of Bank of Italy Survey of Inflation and Growth Expectations.
Note: data points are quarter-specific averages (y-axis) and most recent inflation data (x-axis).
Time period: 2012:3-2019:4.

Table F.1: The drivers of CGR estimate of the effects of the information treatment

	All sample		ELB sample	
(a) $\hat{\theta}$ (CGR)		0.548		0.508
(b) $\hat{\theta}$ (no SectXQtr dummies)		0.558		0.506
(c) $\hat{\theta}_T$	0.733		0.639	
(d) Δ^F	-0.202		-0.193	
(e) $\bar{\pi}^*$	0.819		0.508	
(f) $\Delta^F/\bar{\pi}^*$		-0.247		-0.379
(g) $V(T_{it} \mid I_i = 1)$	0.980		0.537	
(h) $V(T_{it})$	0.814		0.424	
(i) $P(I_{it} = 1)$	0.682		0.687	
(l) Σ_T^1		0.821		0.869
(m) $\hat{\theta}_T \Sigma_T^1 + \frac{\Delta^F}{\bar{\pi}^*}(1 - \Sigma_T^1)$		0.558		0.506

Table reports components of coefficient from regression of firms' future expected inflation (12m) on treatment variable defined as the value of inflation presented to randomly selected firms interacted with a dummy equal to one if the firm belongs to the treatment group. All sample: 2012:3-2019:1; ELB sample: 2014:1-2019:4. See equation (F.6) for further details.

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