Information Flows and Disagreement[*]

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Abstract

The aim of our study is to assess the extent to which the degree of heterogeneity of inflation expectations is driven by the flow of information related to current and future price developments. To that end, we follow three routes: i) we propose different measures of information flow that have either a sender or a receiver perspective; ii) we present empirical results for the US that aim to corroborate the hypothesis that news have the ability to densify expectations, i.e. to reduce forecast heterogeneity; and iii) we augment an otherwise standard model of expectation formation by allowing the individual updating frequency to depend on the observed measure of information flow.

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1 Introduction

The fact that households may have access to differing information sets or as well to different models when forming expectations has for long been rather neglected by macroeconomic theory. This was perhaps a fortunate development, in particular since the advent of the rational expectations hypothesis in the 1970s, since it permitted building analytically elegant modeling frameworks that were tractable, directly usable for policy analysis and reasonably well equipped to match key properties of the data.

Survey data on expectations then became available and have concentrated researchers' attention to the fact that there are high levels of cross-sectional dispersion across agents in terms of information holding, information processing and forecasting ability, but also in terms of behavioral responses to news or policy announcements. Research has then begun to increasingly focus on the determinants and effects of private information and disagreement, a trend that has gained momentum in recent years[1].

Economists have recognized that the additional assumption that tended to come

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[1]Disagreement is shown to be a key driver of asset prices and leverage in the model of He and Xiong (2010), where cash-constrained optimists use their asset holdings as collateral to raise debt financing from less optimistic creditors. This confirms results from a long series of models exemplified by Harrison and Kreps (1978), Chen, Hong and Stein (2002) and Scheinkman and Xiong (2003) in which asset bubbles are generated by a combination of heterogeneous beliefs and short-sale constraints. The contribution of Nimark (2010) is particularly illuminating in this regard, since he proposes an empirical identification methodology of the speculative component of asset prices, more precisely the component arising from heterogeneous beliefs and higher order expectations.

Heterogeneous beliefs, arising from the presence of private incomplete information or rational inattention is also shown to be a driving force of business cycles fluctuations in the macroeconomic frameworks of Woodford (2002) and Mackowiak and Wiederholt (2006).

Sims (2008) analyzes a model in which dispersion of beliefs about monetary policy causes high levels of leverage and can increase or decrease investment, in an environment where uncertainty about investment, common across agents, has no such effects.

As concerns policy, Lorenzoni (2010) shows that disagreement induces a trade-off in terms of aggregate vs. cross-sectional efficiency, such that in order to stabilize aggregate variables, the policy maker induces agents to ignore private signals which would have made them better off. The same result holds in the model of Angeletos and Pavan (2009), except that they show the existence in some contexts of policy rules which can restore constrained efficiency in the decentralized use of information, thus guaranteeing that there are no negative welfare effects associated with the centralized provision of public information. Along similar lines, Gala and Volpin (2010) showed recently that private herding on public information can lead to systematic defaults.

along with the rational expectation hypothesis, namely that information is costlessly available to the entire public and all agents could process all information optimally should in some way be relaxed. Detailed micro-foundations for a model in which information disseminates only slowly through the population have been proposed and popularized by Mankiw and Reis (2001), with a set-up that is now commonly referred to as the *Sticky Information* (SI) model. Besides the model's various implications for aggregate dynamics and the effect of monetary policy, e.g. that monetary policy shocks should impact price inflation with quite substantial a lag, i.e. not contemporaneously as implied by the New Keynesian model set-up [see Taylor (1980), Rotemberg (1982), Calvo (1983)], it implies that agents should have different expectations which is due to the, so-assumed, staggered diffusion of information. Only a fraction of agents will update their expectations every period, while the remainder of the population continues to form expectations based on outdated information.

The SI model setting has found some support, though in a somewhat different conceptual framework, by Carroll (2003a/b): it is an *epidemiological model* (EPI) that parallels the spread of information through the population with that of a disease; the assumption is that individual agents do not form an expectation on their own but rather adopt, i.e. get infected with, the views of professional forecasters that are conveyed via the media.

The difference between the EPI and the SI model is that the former lets agents update toward professional, and the latter toward the latest rational forecast that agents form themselves[2]. The calibration and simulation exercise from the second part of our paper attempts to shed light on these models' properties.

Another strand in the literature, an early one, that our study is related to, is the one by McCombs and Shaw (1972) on the agenda-setting function of mass media. The central point is that media can have a marked impact upon people's awareness of certain topics, where one assumption is that concentration on salient issues leads the population to perceive this issue as more relevant. Importantly, the theory rests also on the assumption that media can shape news in a way that may distort reality to some extent. As most of the related work that has appeared since McCombs

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[2]Yet another theoretical framework has been proposed by Roberts (1997); here, the updating is done with reference to the past realization of inflation.

and Shaw, they explore the theory in a political context and find a positive relation between news intensity and what voters found most relevant in political campaigns. More recent work that relates to our present study has been done by Eife and Coombs (2007), who analyze the role of media and communication in shaping the public's perception of current price developments and argue that increasing inflation misperceptions following the euro cash changeover could possibly have been avoided if policy makers had made the public more aware of the fact that its perception of current inflation was unreasonably high.

From an empirical perspective, there are yet relatively few papers analyzing what the determinants of disagreement are. An important first reference is Mankiw et Al. (2003) who present stylized facts and empirical regularities in and among survey measures of disagreement for the US, and as well with a view on their relation to macroeconomic variables. Moreover, they demonstrate that the SI model is capable of explaining observed patterns in the level and the dispersion of survey expectations. One concrete finding in Mankiw et Al. (2003), however, is that the SI model is not able to replicate the apparent positive relationship between disagreement and level inflation that can be found in the data. We shall later argue that this finding, and the model's inability to reproduce the empirical regularity, may be an artefact of the chosen measure of disagreement.

Further empirical work towards finding the determinants of disagreement has been provided by Maag and Lamla (2009) who adopt a Bayesian learning model setting in which media coverage of inflation affects forecast disagreement by influencing both the information sets as well as the predictor choice. In their model, agents update their prior expectations about inflation by absorbing news transmitted by television and newspapers, while these media reports are known even by the public to contain noisy signals about future inflation. In this sense then, the typical household faces a signal extraction problem which is solved through Bayesian updating. Moreover, they allow for heterogeneous forecasting models, along the lines of Kandel and Zilberfarb (1999). The approach is innovative particularly with regard to the analytical differentiation between the volume of news and their content: more news shall induce the agent to put less weight on prior beliefs, but it is the specific content which determines heterogeneity and disagreement at aggregate level. Thus, in terms

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of testable implications the model suggests: i) both a higher volume of media reporting and a lower heterogeneity (information entropy) of the statements about inflation lead to lower forecast disagreement, as agents converge more and more to the same information set and ii) if all media reports contain the identical message, the variance of the noise component collapses to zero, agents end up choosing identical predictors and at aggregate level the cross-sectional dispersion of expectations decreases. The empirical findings that we present for the US are somewhat in contrast to Maag and Lamla (2009) who conduct their analysis for households and professional forecasters in Germany: unlike for Germany, we find that disagreement among US citizens does depend on media coverage; a more intense information flow makes people agree more.

The contribution of our paper can thus be seen along three dimensions: first, we present a set of alternative schemes to measure information flow and in particular do we distinguish between a *sender* and a *receiver* perspective of information[3]. It turns out that for the US, the two quite distinct sources of information, one representing the sender and the other one the receiver side, give us very similar measures of news intensity. This provides us with confidence in using one or the other measure for subsequent empirical analysis and also corroborates the avail of such measures for, say, the euro area, where the receiver measure, as such, is not available. Second, we present a set of regression results which aim to test the hypothesis that information flows have the ability to impact the cross-sectional distribution of expectations. We find that the more intense the information flow, the less the agents disagree about the future. And third, we augment the standard micro-founded models of disagreement by allowing the updating frequency to be time-varying, in particular by making it a direct function of the information flow, to then show that the sticky information as well as the epidemiological model set-up are better able to replicate the observed patterns in disagreement relative to the original model settings where the updating frequency was assumed to be constant through time.

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[3]Our work also comes close to the approach of Veldkamp (2006) in terms of the quantification of the sender side of the information flows through measuring mass media news intensities.

2 Data and methodology

The main data source that our empirical study is referring to is the Michigan Survey of Consumers. We draw upon the cross-sectional archive of monthly survey waves, each containing a set of recurrent questions tracking different aspects of consumer attitudes and expectations and covering the period between January 1987 and December 2009. The monthly cross-sectional samples cover a pool of approximately 500 individual respondents, chosen such as to be representative of the US population excluding Alaska and Hawaii. The surveys are released during the last week of a month.

Second, we use macroeconomic data that we retrieve from the St. Louis Fed's FRED$^©$ database. Our data set comprises the consumer price index for all urban consumers (*CPIAUCNS*), the real gross domestic product (*GDPC96*) and the effective federal funds rate (*FEDFUNDS*). All of the three series cover the period between January 1955 and December 2009, with inflation and the interest rate having monthly and GDP a quarterly frequency. We construct a measure of the output gap by first interpolating the quarterly GDP series to monthly frequency and then identifying the cyclical component by means of an HP filter. The output gap series is computed as the log difference between the cyclical and the trend component that we obtain after having applied the filter.

For obtaining measures of news intensity we refer to the Michigan Survey, to Google's *Insights for Search* tool and to the professional news service provider *Factiva*. We obtain alternative measures of information flow that all have a monthly frequency and cover the period from January 2004 to July 2010. Further details on the construction of the information flow variables follow in Section 2.2 below.

Finally, quarterly data on inflation expectations by professional forecasters are obtained from the Survey of Professional Forecasters which we convert to monthly frequency. The reference series measures expectations of changes in consumer price inflation (*CPIA*) at the one-year horizon and covers the period from January 1982 to June 2010. In our simulations, we use the mean of the cross-section of responses that were recorded over time.

2.1 Quantifying disagreement

The Michigan Survey of Consumers contains two questions that relate to price expectations, based upon which we construct measures of central tendency and dispersion of expected inflation.

Question **PX1Q2** (recoded as **PX1**) reads as follows:

By about what percent do you expect prices to go up/down on the average during the next 12 months?

Respondents are supposed to provide a point estimate in percent or may choose to answer *don't know*. Based on the cross-sectional distribution of answers to this question, we compute mean, median, standard error, and the interquartile range, with the latter two being measures of dispersion, disagreement respectively, to which we refer to as *quantitative* disagreement. Such quantitative measures have been used e.g. in Carroll (2003) and Mankiw and Reis (2003).

An alternative measure of disagreement can be derived from question **PX1Q1**, which is phrased as follows:

During the next 12 months, do you think that prices in general will go up, or go down, or stay where they are now?

Respondents can choose between four answer categories: *Go up* (e^1), *same* (e^2), *go down* (e^3), or *don't know*. To quantify disagreement we here employ the following measure:

$$\sigma_t^e = \sum_{i=1}^{2} F_t^{e,i} \left(1 - F_t^{p,i}\right) \tag{1}$$

where $F_t^{e,i}$ are the cumulative relative frequencies for the i-th answer category at time t. Note that the third answer category is excluded from the sum since the cumulative frequency is 1 and therefore does not contain additional information on the distribution of the response shares[4].

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[4]The first three answer categories have been rescaled so as to sum to unity at every point in time, i.e. the *don't know* answer share is evenly distributed among the three remaining categories.

This measure has been proposed by Lacy (2006) to whom we refer for details. Importantly, the measure is ordinal in nature, i.e. it does not require one to assume that the distance between categories be equal. Other statistics such as plain standard deviation measures shall not be applied here because one would have to have a variable measured at interval scale. The distances between response categories cannot be quantified, nor shall we assume that they are equally far from one another. We normalize the measure such that it ranges between zero and one. The maximum refers to a fully polarised distribution (as Lacy (2006) refers to this case) in which all responses fall into two response categories to equal shares. The other extreme is when all responses fall into a single category (full agreement); the measure will reach its minimum at 0 in this case. To this ordinal measure of disagreement we refer to as *categorical* in the following.

Figure 1 shows the central tendency measures (mean and median) from the quantitative question along with actual inflation. Figure 2 shows the two quantitative measures (standard deviation and interquartile range) along with the categorical (ordinal) measure of disagreement.

The categorical disagreement measure, we argue, is at least as appropriate as the interquartile range for quantifying the belief heterogeneity. The only paper that we are aware of that employs a similar ordinal measure of dispersion is Maag and Lamla (2009); it is the so-called index of qualitative variation that these authors compute.

In Figure 1, one can see a strong positive relationship between level inflation and the quantitative measure of disagreement; this empirical regularity has been documented by various authors, including e.g. Mankiw et Al. (2003). The strong positive correlation is interpreted perhaps righteously as reflecting the fact that inflation uncertainty rises with higher levels of inflation. We think, however, that as far as the macroeconomic implications on consumer behavior are concerned, drawing conclusions on the base of this relationship may be misleading. First of all, consumers answering a telephone interview question on inflation point forecasts may not be very precise in their quantitative assessment of the expected level of price inflation, while their answer is at least as (or even more) reliable and less subject to noise when they are asked to do an ordinal (categorical) choice. For example, about 2% of agents state that they expect prices to go down, with - at the same time - their

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answer to the quantitative question being a figure somewhere above 5%. So, if one had to decide which of the two answers to trust more, we would favor the ordinal one.

And not least, in terms of the economic interpretation, the same extent of dispersion, say, 5 percentage points, around an average inflation expectation of, say, 10%, versus that same dispersion around a 1% level may reflect quite different realities and generate quite different consumer behavior, since the latter would imply that some portion of agents would even consider deflation likely to occur.

2.2   Quantifying information flows

In order to measure the flow of information related to current and expected future price developments we follow three routes.

First, we refer once more to the Michigan Survey, that is, to questions **NEWS1** and **NEWS2**. They read as follows:

During the last few months, have you heard of any favorable or unfavorable changes in business conditions? What did you hear?

Respondents can choose two items out of 80, six of which we consider being related to prices, price inflation respectively.

$\ldots$

n^{31} *Lower/stable prices, less inflation*
n^{32} *Higher prices, inflation is good*
n^{37} *Other references to prices/credit*
n^{71} *Prices falling, deflation*
n^{72} *Prices high, inflation*
n^{77} *Other price/credit references*

$\ldots$

n/a *don't know*

Based on the answers to this question we compute a monthly share of agents who were considering changing price conditions relevant. We think of this first measure

of information flow as reflecting a **Receiver** perspective. In the following we will refer to to this measure as *survey-based news*.

Second, we use Google's *Insights for Search* tool which can be used to analyze search patterns for optional sets of geographical areas. The keyword that we instruct the search engine to analyze is *inflation*. We obtain a weekly time series in the form of an index, with the maximum over the sample period being normalized to 100. The weekly frequency is converted to monthly by taking period averages. Of this second measure of information flow we think of as also being reflective of the **Receiver** perspective, though it has somewhat different a flavor compared to the survey derived measure since agents put own effort into the search via Google.

Third, we employ the inflation news intensity measure from Badarinza and Buchmann (2008). The professional news service provider *Factiva* allows us to retrieve the number of articles that contained the term *inflation* in their headlines or lead paragraphs which we then divide by the number of news contained in the parent directory (which is supposed to count all economic news). Thus, we obtain a ratio of inflation-related news appearing in print and online media with a monthly frequency back until January 1990. This last source of information flow can be thought of as reflecting the **Sender** perspective of information flow. We will henceforth refer to it as *public news*.

Figure 3 and 4 illustrate how the two receiver and the one sender information flow series compare. In particular the survey-based receiver-side measure and the Factiva sender measure of information appear to follow very similar paths over time; during the 2005-2009 period, the correlation between the two is .81. Deviations from the Google news intensity measure relative to the other two news measures are somewhat more pronounced; its correlation to the survey-based and the public news measures equals .4 and .5, respectively.

3 Regression results

The starting point of our present analysis and the counterpart to the results obtained for euro area data in Badarinza and Buchmann (2009) is the very pronounced

negative co-movement depicted in Figure 5 between categorical disagreement and our measure of news intensity. This effect is in line with the predictions of benchmark theoretical models of expectation formation which draw on either informational frictions or some general form of Bayesian learning.

However, the simple univariate inspection of this co-movement property may be subject to an omitted variable problem; news co-move positively with the level of the inflation rate (the common sample correlations are .4 and .3 respectively for public and survey-based news) and so the decreases in disagreement may not be causally driven by a more intense information flow but simply be explained by the fact that agents either put more effort into updating their information sets (the Google search frequency correlates with inflation by a factor of .7) or that news media agencies have a reporting bias towards high (or rising) inflation levels. Also, we have to be careful when drawing conclusions on the survey-based news intensity, since it also reflects information/news that agents have purposely chosen to be exposed to. This decision of information consumption and, moreover, the decision to choose from a long list of 80 items one of the 6 relating to price inflation, may thus not be exogenous to the individual expectation formation mechanism.

In order to properly control for these effects, we include in our regressions the inflation level, the square of the inflation level and the square of inflation in first differences as a proxy for short-term inflation volatility.

Table 2 shows the first set of results. Full-sample period estimates suggest that the effect of inflation-related survey-based news is negative and significant at the 1% and 5% levels respectively on both quantitative and categorical disagreement. For the sub-period from 2000 until the end of the sample, this effect remains negative and significant only in the case of the categorical disagreement measure. In terms of magnitudes, the effect is measured to be more pronounced compared to the full-sample estimate. Figure 6 confirms that the coefficient estimates from these benchmark models are rather stable over time.

As Mankiw and Reis (2003), we find the relationship between quantitative disagreement and the inflation level to be positive, with the corresponding p-value suggesting that the effect is significant at least at the 1% level. For the sub-sample from

2000-2009, however, we see the sign switching to negative and the effect being significant at the 5% level. When referring to the categorical measure of disagreement, level inflation does not appear to entail statistically significant effects on disagreement.

Unlike for the effect of the level of the inflation rate, the effect of short-term inflation volatility appears robust. The magnitudes of the estimated normalized coefficients are comparable across different model set-ups: the estimates suggest a significant positive effect, irrespective of the choice of the disagreement measure and for the full- and both sub-sample periods. We interpret this as strong evidence in favor of the hypothesis that higher fundamental uncertainty generates higher disagreement, as agents either form expectations based on outdated information sets, use different forecasting models or have differing product groups in mind when thinking about the likely evolution of the price level in the near future.

The magnitude of the effects that variation in the explanatory variables induce for disagreement can be directly compared because the coefficients have been normalized: a 1 standard deviation (STD) upward move in received news about inflation result in a 0.13 STD fall in categorical disagreement for the sub-sample from 2000-2009. The effect of a 1 STD rise in inflation volatility, c.p., induces a 0.18 STD increase in categorical disagreement and therefore exerts a more pronounced effect than all other right hand side variables in the model.

In Tables 3 and 4 we report results for regression models that have, respectively, quantitative and categorical disagreement as the dependent variable. We now take the perspective of the sender of information and include the public news series as an explanatory variable.

The results in Table 3 suggest that the variation in information flow does not seem to induce significant variation in quantitative disagreement, with the exception of the model that excludes the lag of the dependent variable. Since quantitative disagreement appears to be quite persistent as indicated by the estimated AR(1) coefficient (0.83) with its corresponding p-value and the increase in the model's R-square from 25% to 78% when including the lag, the effect of news can thus not be separately identified.

When considering instead categorical disagreement in Table 4, information flows

exert a significant negative effect irrespective of the chosen sample period and irrespective of whether or not a lag is included in the model. The inflation level also seems to have a negative effect, which is not surprising, however, given that as the inflation level moves in and out of a certain ordinal category, agent's expectations are also driven more or less in the same direction, without this actually saying much about true behaviorally relevant changes in the heterogeneity of beliefs.

The marginal contribution of the news variable to the fraction of variation in categorical disagreement explained by the model (differences in respective R-square measures) ranges between +14 and +15 percentage points for the 1990-2009 and 2000-2009 sample periods. For the sample as a whole, the econometric specification which includes the lagged dependent variable suggests that a 1 STD intensification of the flow of information related to price inflation is associated with a 0.04 STD fall in aggregate disagreement.

These latter estimation results confirm our previous estimates based on euro area data and generally support the view that unexpected changes in information flow have the potential to densify expectations, i.e. to generate more agreement among consumers about the likely future path of inflation.

4 Models of information diffusion

4.1 Theoretical framework

In this section, we attempt to give a comparative overview of what different models of expectation formation imply regarding the level of inflation expectations and the level of disagreement. The economy is assumed to consist of an infinity of agents which form expectations about monthly values of aggregate variables subject to their individual (possibly cross-sectionally heterogeneous) information sets. In each period, there is thus a continuum of individual forecasts.

Assume macroeconomic aggregates evolve according to the VAR(12) law of motion:

$$x_t = \Phi_1 x_{t-1} + \ldots + \Phi_{12} x_{t-12} + \varepsilon_t \text{ with } \varepsilon \sim N(0, \sigma), \qquad (2)$$

where x_t is a vector of observable (de-meaned) variables:

$$x_t \equiv \begin{bmatrix} \pi_t \\ r_t \\ y_t \end{bmatrix},$$

with π_t being the inflation rate, r_t the Federal Funds rate and y_t the economy-wide output gap.

By appropriately stacking variables and lags, we represent the law of motion in VAR(1) format:

$$X_t = AX_{t-1} + B\epsilon_t, \text{ where } X_t \equiv \begin{bmatrix} x_t \\ x_{t-1} \\ \vdots \\ x_{t-11} \end{bmatrix} \text{ and } \epsilon_t \equiv \begin{bmatrix} \varepsilon_t \\ \varepsilon_{t-1} \\ \vdots \\ \varepsilon_{t-11} \end{bmatrix} \qquad (3)$$

At this point, the question arises as to how agents process this information in order to come up with point and categorical forecasts of the inflation rate (or any aggregate variable) twelve months ahead.

We consider four different expectation formation schemes:

- **Rational expectations.** The optimal time t forecast, conditional on the full set of observable variables and their history corresponds to applying the expectations operator on the law of motion and conditioning on time t information. If all agents share the same time t information, their forecasts are all identical and the aggregate average expectation is:

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$$E_t X_{t+12} = A^{12} X_t \tag{4}$$

- **Sticky information.** This version of the model has at its heart the information diffusion mechanism for which Reis (2003) derives explicit micro-foundations. Agents are assumed to update their information sets infrequently, with only a fraction δ_t having perfect knowledge of the whole observable vector x_t and a fraction $(1 - \delta_t)$ building expectations conditional on their $t - 1$ individual information set (i.e. not necessarily updated at $t - 1$, but at some point in the past). On aggregate, the evolution of the average expectation is given by:

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\begin{aligned}
E_t^{SI} X_{t+12} &= \delta_t E_t X_{t+12} \\
&\quad + (1 - \delta_t)\delta_{t-1} E_{t-1} X_{t+12} \\
&\quad + (1 - \delta_t)(1 - \delta_{t-1})\delta_{t-2} E_{t-2} X_{t+12} \\
&\quad \cdots \\
&= \begin{bmatrix} \delta_t & (1 - \delta_t)\delta_{t-1} & (1 - \delta_t)(1 - \delta_{t-1})\delta_{t-2} \cdots \end{bmatrix}
\begin{bmatrix} A^{12} X_t \\ A^{13} X_{t-1} \\ A^{14} X_{t-2} \\ \vdots \end{bmatrix} \\
&= \delta_t A^{12} X_t + (1 - \delta_t) A E_{t-1}^{SI} X_{t+11}.
\end{aligned} \tag{5}
$$

- **Sticky expectations.** In this version of the model, agents again update only infrequently, with only a fraction δ_t forming expectations rationally based on time t information; We assume, however, that individuals amounting to a fraction of $(1 - \delta_t)$ deviate from strict rationality in the sense that they stick to their period $t - 1$ forecast, so they don't even bother (e.g. as an outcome of inattention) to either update the information set or build a new forecast based on outdated information. One can think of this framework as implying that agents, when they update the information set, form a certain expectation

about one-year ahead inflation, to which they then stick up until the infinite future, provided at some point they update again. There are no explicit micro-foundations for this type of behavior in the literature and indeed we consider it a rather extreme case of deviation from rationality (especially the fact that agents are assumed to not perceive the existence of a term structure of inflation expectations). We think, however, that the sticky expectation scheme may reflect a key aspect of inertial behavior and so we at least want to give it a chance and ultimately let the data speak. At the aggregate level, expectations then evolve as follows:

$$E_t^{SE} X_{t+12} = \delta_t A^{12} X_{t+12} + (1 - \delta_t) E_{t-1}^{SE} X_{t+11} \tag{6}$$

- **Epidemiological diffusion.** Finally, we consider the model by Carroll (2003a/b), which again is a rather significant departure from rational expectations: no single agent (consumer) actually observes the set x_t of macroeconomic aggregates, but individuals amounting to a fraction δ_t have access to public media through various channels of information transmission, where they read a certain forecast coming from professional forecasters; the remaining fraction $(1 - \delta)$ is inert in the sense that their time t forecast is derived based on the published professional forecast at some point in the past. If we denote by E^{prof} the published professional forecast, the average aggregate expectations evolve according to the process:

$$E_t^{EPI} X_{t+12} = \delta_t E_t^{prof} X_{t+12} + (1 - \delta_t) E_{t-1}^{EPI} X_{t+11} \tag{7}$$

4.2 Information flows

As can be seen above, we intend to let the share of the population that updates its beliefs to be *time-varying*. In order to do so, we will employ the measures of news intensity proposed in Section II as a proxy.

The question, however, arises as to how one can quantify, identify respectively, the δ, that is, how some news intensity measure can be mapped into δ_t. Since there is no previous reference in the empirical literature on how this mapping could be accomplished, as a first step we take the survey-based news measure at face value and assume it be equal to δ_t. The survey-based news variable measures the fraction of respondents to the Michigan Survey which state that they had received news about inflation during the relevant period. We consider the measure a reasonable first approximation of δ_t.

We will later consider alternatives to this strict identification of δ by the survey-based news measure because it may well be subject to significant sample selection and measurement issues[5]. The survey-based news measure in Figure 3 illustrates how δ may have been varying over the sample period: during the late 1970s and early 1980s, the updating share of the population rises to about 30% per month; during the 1990s it is more or less constant at round about 6% and during the latter part of the 2000s decade it rises to some 50%.

4.3 Expected inflation

As Mankiw et al. (2003) have shown, the sticky information model is highly successful in matching the observed time path of consumer inflation expectations, with a correlation coefficient of 0.8 for the whole sample. They find an optimal (constant!) stickiness parameter of $\delta = 10\%$. Our experiments confirm these findings for the extended sample: when holding δ constant and including also data for the last years, the correlation coefficient stays at above 0.8 and we find an optimal δ of about 10%.

Similar results hold for the sticky expectations model (see Table 4): the full sample correlation between model-implied expectations and survey expectations equals .83 and the stickiness parameter rises to $\delta = 12\%$. Thus, the results appear to speak somewhat in favor of the sticky information rather than the sticky expectations model scheme.

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[5]In order to ensure that the mean of δ is equal to 10% (see Section X.X), we add a constant term of 2.9% to the news measure.

Splitting the sample into sub-periods sheds additional light on the performance of the different model settings: during the high inflation period of the early 1980s, both models fit the data very well, that is, much better than on average for the whole sample, with sticky information performing slightly better. When we look at the period up until September 2001, the performance of the sticky information model remains rather constant, while it is also the epidemiological model that manages to explain survey expectations pretty well (a correlation coefficient of .6). The information spread by professional forecasters appears to having also become more relevant for consumer expectation formation over time.

Turning to the effect of information flows, we observe that allowing for time variation in the updating share improves the models' ability to explain the data, albeit not for all sub-samples. First, during the years of high inflation, Figure 7 shows that accounting for the fact that more than 30% of agents actually update, improves the model's ability to explain the rather fast adjustments observed in the data. Second, during the low-inflation years ensueing after the mid-1980s, accounting for information flows seems to be important for understanding why, after increases in the level of inflation, to which agents seem to adjust quite quick, there is a prolonged period of inertia during which expectations remain at high levels. After all, the improvement of model fit during this period is truly marginal, but graphical inspection (see Figures 7, 8 and 9) shows that especially in the wake of high news intensity, expectations seem to be sticky which can be well explained by the fact that the share of people who update is falling sharply. The opposite conclusion holds however for the epidemiological model: when the updating share is allowed to depend on news intensity, the explanatory power of the model decreases. We see this as evidence against the hypothesis that the media transports expectations of professional forecasters to the public.

4.4 Disagreement

We now turn to analyzing the model-implied measures of disagreement. We measure disagreement as the standard deviation of the cross-sectional distribution of forecasts, such that for some period t we have different cohorts, each of them weighted

by the corresponding updating weight (see derivations in Equation (5)). Again, as demonstrated in Mankiw et al. (2003), the sticky information model does a fairly good job at matching the observed time variation in quantitative disagreement (i.e. the cross-sectional standard deviation of point forecasts), with a correlation coefficient of .52 for the full sample and even of .7 for the first sub-period (see middle panel of Table 1). However, during the low-inflation episode, the sticky-information model (and also the other two models) have a very hard time matching the data which we attribute to the fact that any disagreement which may have occurred during this period was not the result of infrequent updating (since anyway inflation was not varying a lot), but of some other underlying source of noise. Accounting for news improves the model fit slightly, but still we see no reason to believe that during this period belief heterogeneity was driven by the infrequent updating of information sets or forecasts. For the most recent period, however, there seems to be clear evidence of stickiness playing a role, with all models delivering a correlation coefficient between .3 and .6. When allowing δ to be varying over time, the model fits decrease substantially for most sub-periods, which we think may again reflect that quantitative disagreement is not mainly driven by stickiness.

A quite different picture emerges if we analyze categorical disagreement instead. First, all three models appear to perform better at accounting for time-variability in categorical than in quantitative disagreement, at least during the second and third sub-sample period. Second, the effect of letting δ to be time-varying is very pronounced and it improves the models' fit significantly. Particularly pronounced is the improvement for the epidemiological model, which the data on the expectations level seems to prefer during these sub-samples. Overall, however, the categorical disagreement data tends to favor the sticky expectations model, across all sub-sample periods. Graphically, we can observe e.g. in Figure 11 that accounting for information flows improves the model's performance in explaining observed patterns significantly, especially during the 2007-2009 crisis period.

5 Conclusions

to be completed

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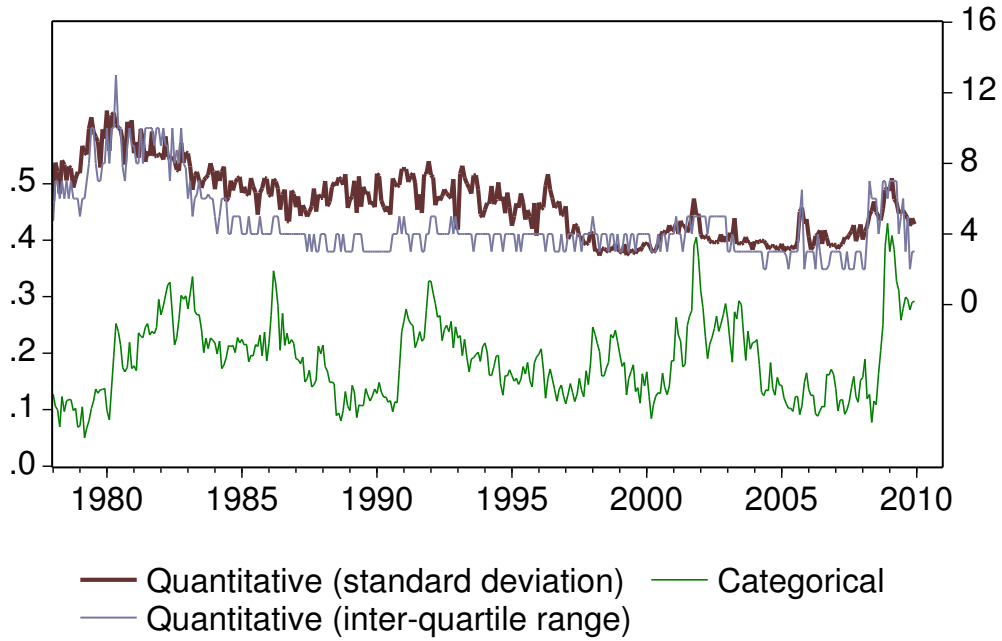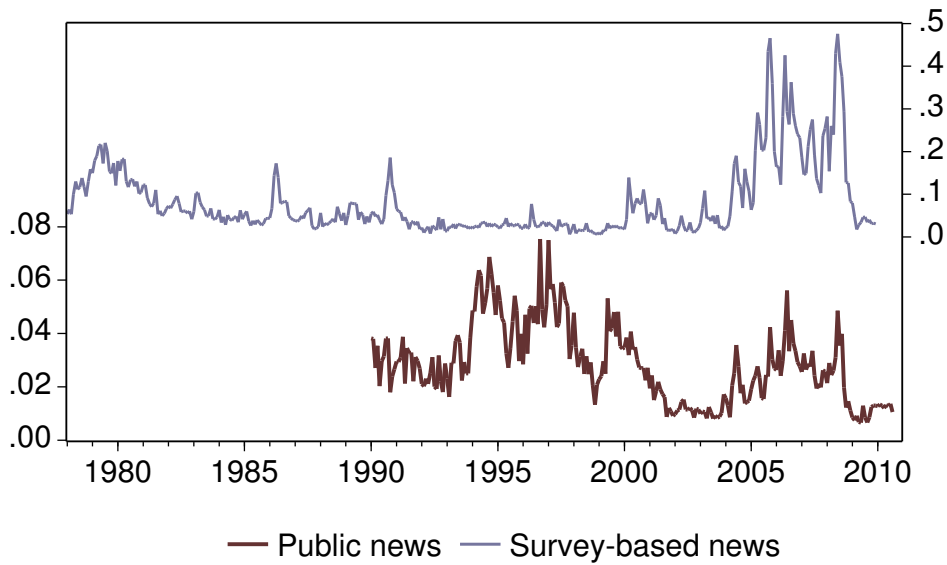
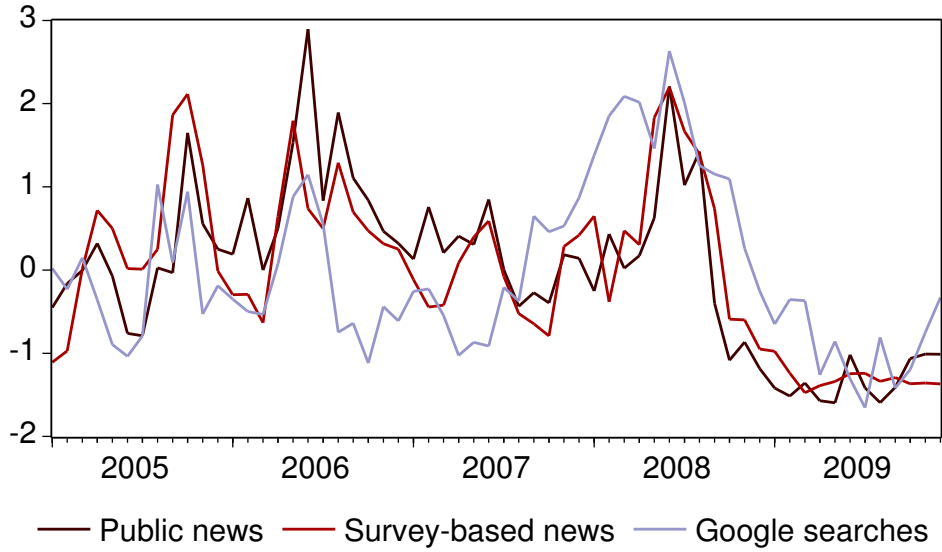# Appendix

Figure 1
Quantification of expectations
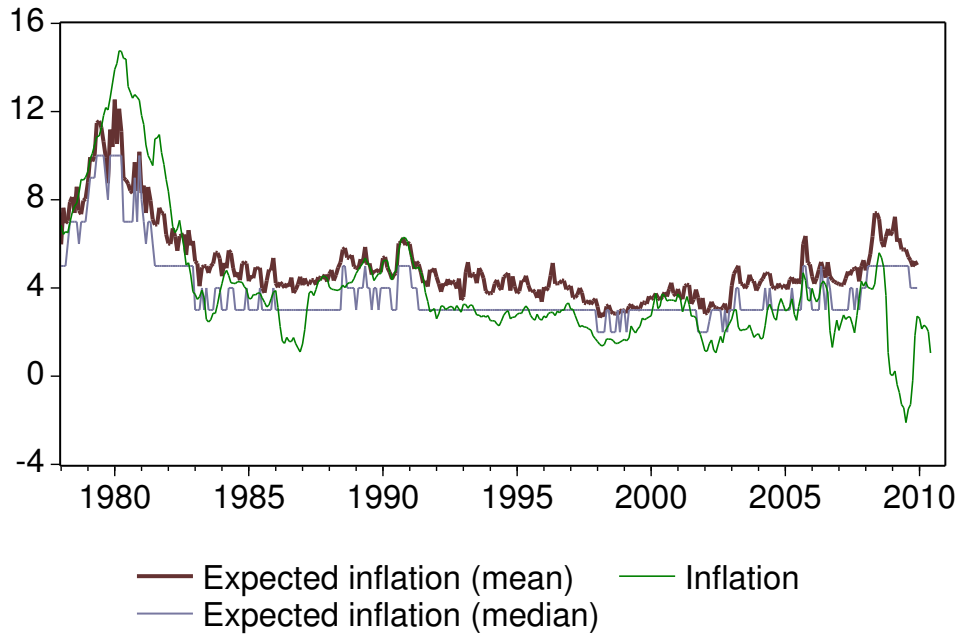
Figure 2
Quantification of disagreement

Figure 3
Comparison between the two measures of inflation-related news

Figure 4

Sender vs. receiver perspective

Note: The Google series is the year-on-year change computed from raw search frequencies. All variables have been normalized by subtracting their mean and dividing by respective standard deviations.

Figure 5

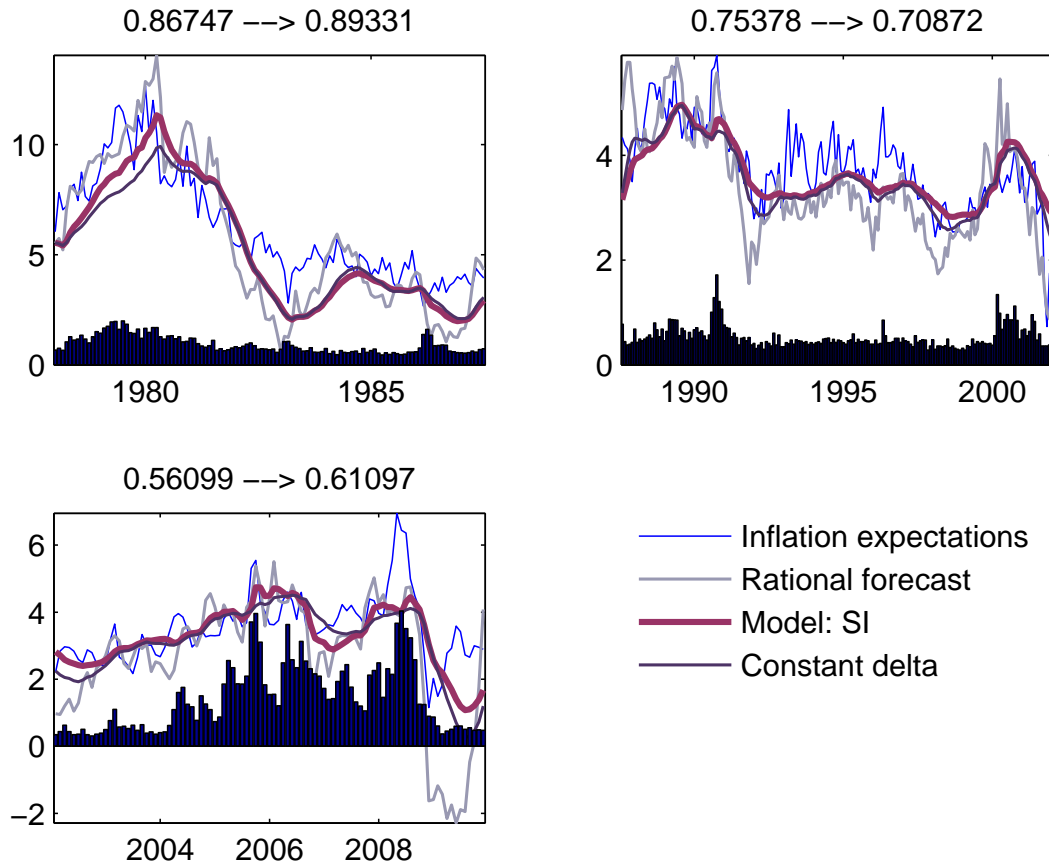Co-movement between news intensity and disagreement
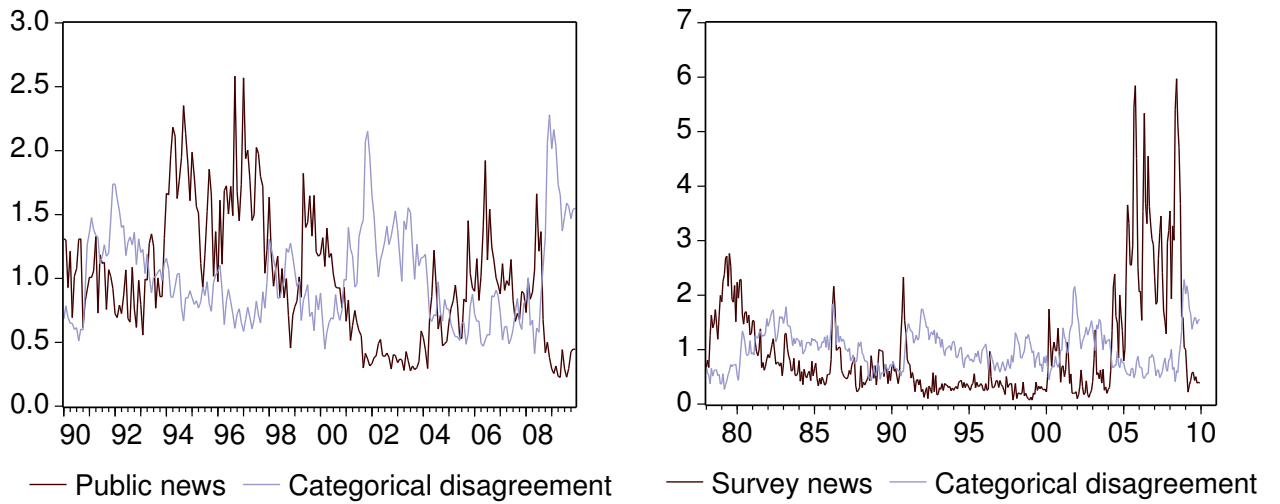
Figure 6
Parameter stability

Lagged

Survey news

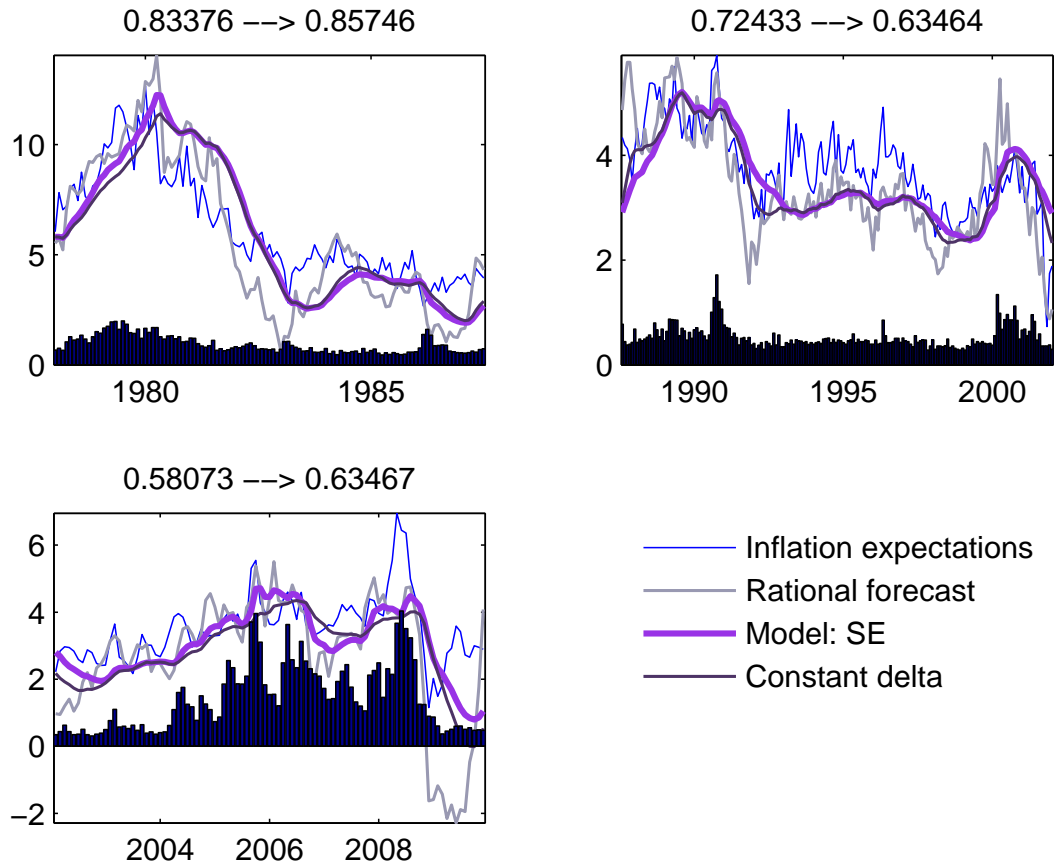## Inflation

Inflation volatility
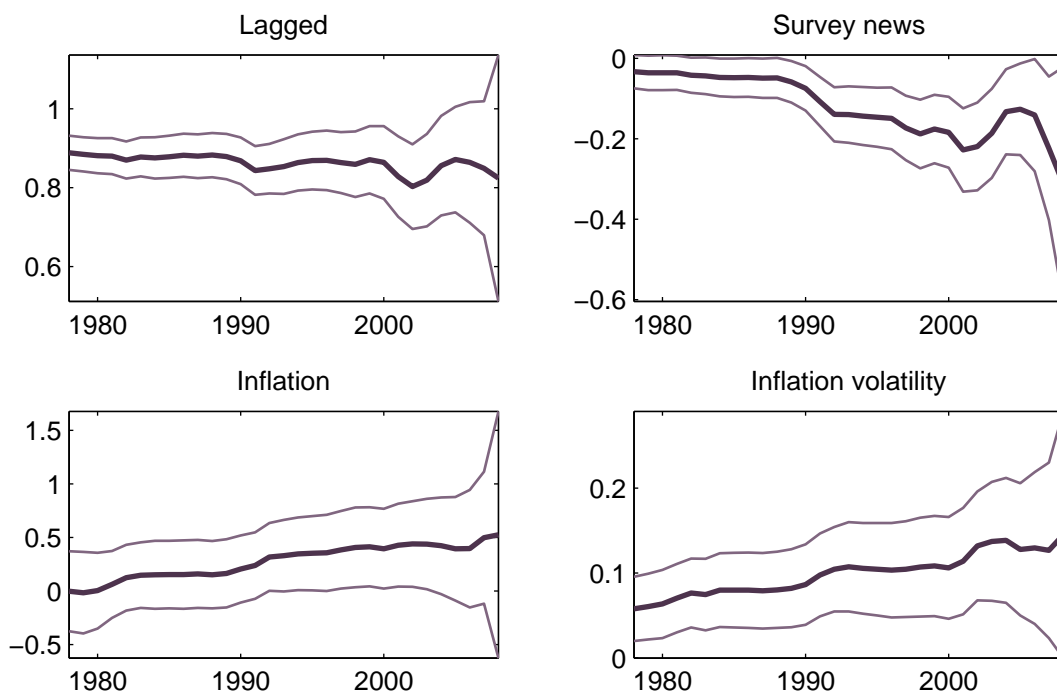
Note: The blue line shows the evolution of normalized coefficients from contracting-window regressions of categorical disagreement on survey-based news, inflation controls and an AR(1) term. The first point on the line thus corresponds to a full sample regression. Gray lines are 90% confidence bands computed from HAC (Newey-West) robust standard errors.

Figure 7
Sticky information model: inflation expectations

Note: The blue line is the inflation expectation as caputured by the quantitative question contained in the Michigan Survey; the gray line is the rational expectation; the red line shows the model-implied evolution of expectations when δ is time-varying and the thin black line corresponds to the case when δ is held constant at 10%. The vertical blue bars depict the time variation in δ (multiplied by a factor of 10 for better readability).

Figure 8

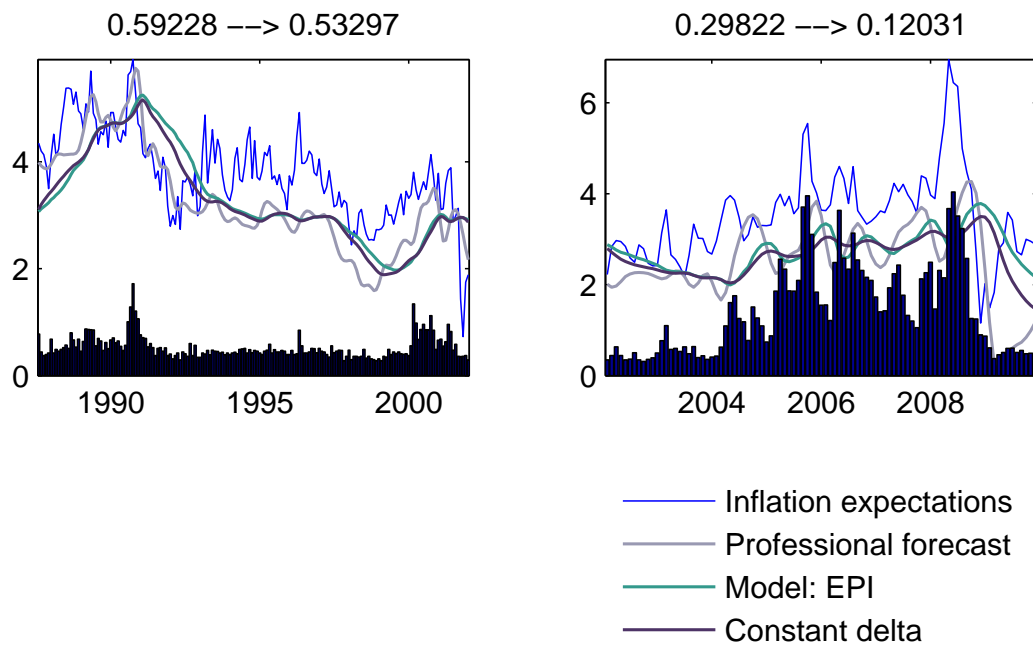Sticky expectations model: inflation expectations

Note: The blue line is the inflation expectation as caputured by the quantitative question contained in the Michigan Survey; the gray line is the rational expectation; the magenta line is the model-implied inflation expectation when δ is time-varying and the thin black line corresponds to the case when δ is held constant at 10%. The vertical blue bars depict the time variation in δ (multiplied by a factor of 10 for better readability).

Figure 9

Epidemiological model: inflation expectations

0.59228 --> 0.53297 0.29822 --> 0.12031

— Inflation expectations
— Professional forecast
— Model: EPI
— Constant delta

Note: The blue line is the inflation expectation as captured by the quantitative question contained in the Michigan Survey; the gray line is the rational expectation; the green line is the model-implied inflation expectation when δ is time-varying and the thin black line corresponds to the case when δ is held constant at 10%. The vertical blue bars depict the time variation in δ (multiplied by a factor of 10 for better readability).

Figure 10
Sticky information model: disagreement
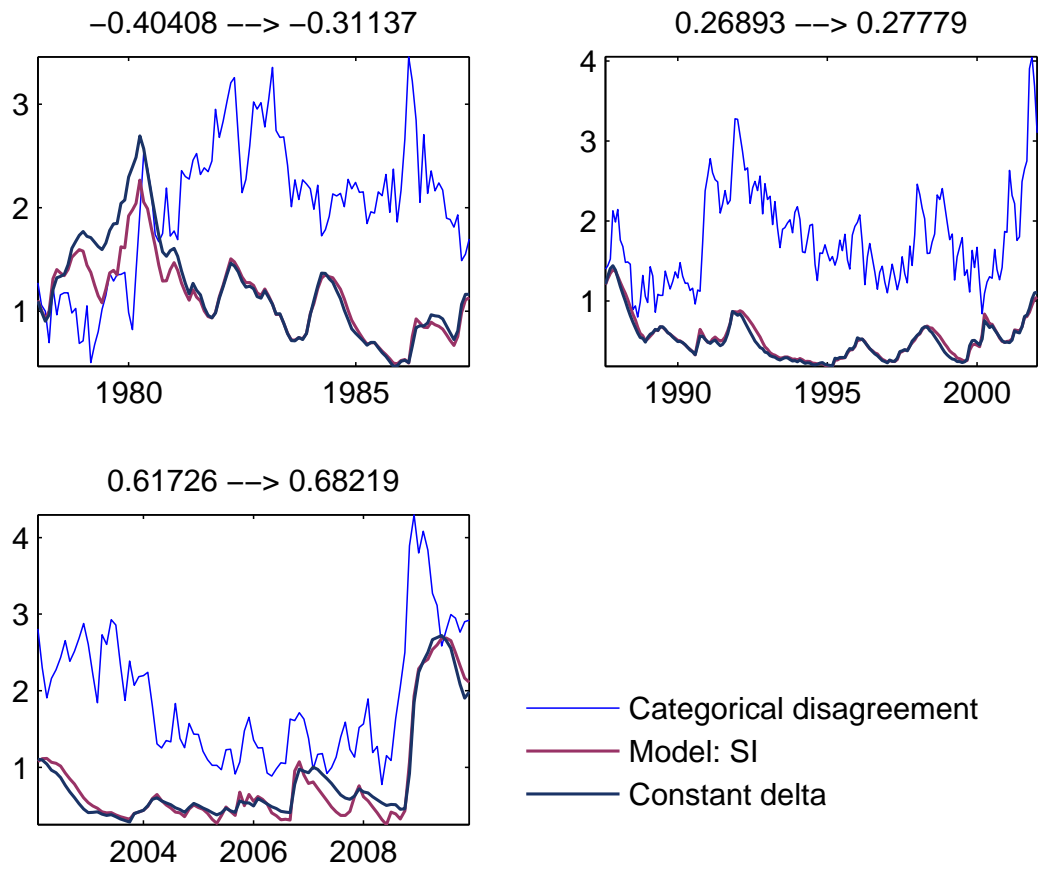
Note: The blue line is the quantified categorical disagreement based on actual Michigan Survey data, multiplied by a factor of 10 for better readability; the red line shows the model-implied disagreement when δ is time-varying and the thin black line corresponds to the case when δ is held constant at 10%.

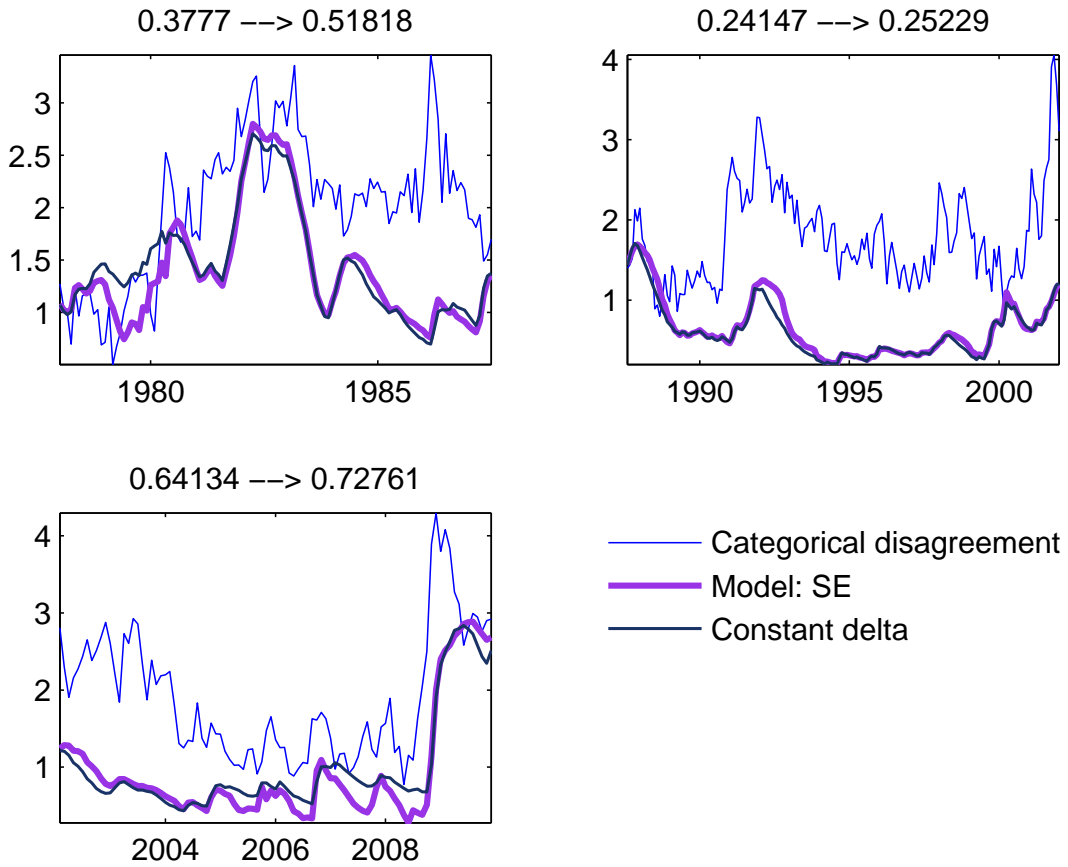**Figure 11**
Sticky expectations model: disagreement

Note: The blue line is the quantified categorical disagreement based on actual Michigan Survey data, multiplied by a factor of 10 for better readability; the magenta line shows the model-implied evolution of disagreement when δ is time-varying and the thin black line corresponds to the case when δ is held constant at 10%.

Figure 12
Epidemiological model: disagreement

| 0.29706 --> 0.30051 | 0.359 --> 0.41291 |

Categorical disagreement
Model: EPI
Constant delta

Note: The blue line is the quantified categorical disagreement based on actual Michigan Survey data, multiplied by a factor of 10 for better readability; the magenta line shows the model-implied evolution of disagreement when δ is time-varying and the thin black line corresponds to the case when δ is held constant at 10%.

Table 1

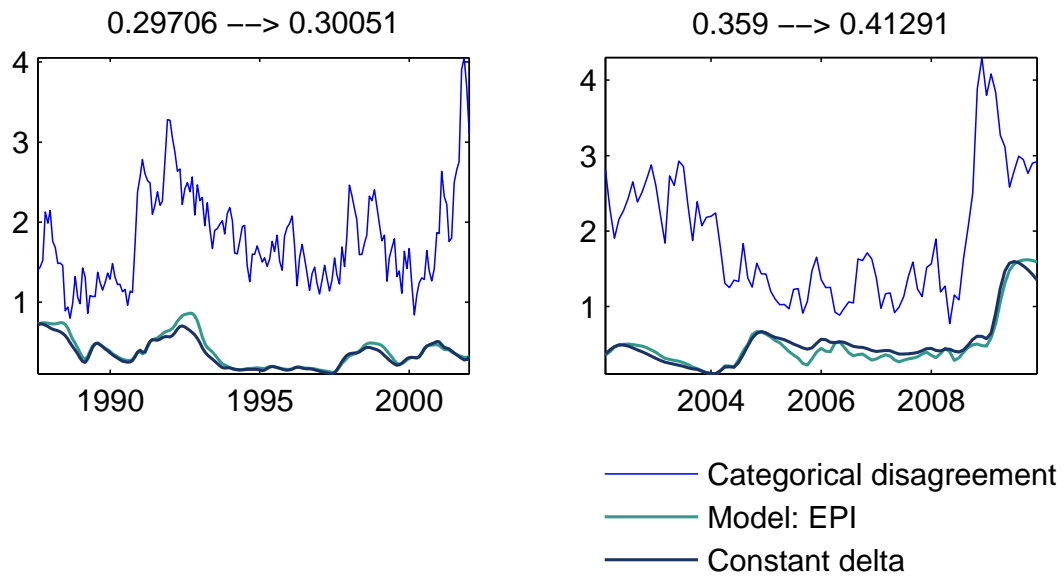Disagreement and survey news

	Quantitative disagreement		Categorical disagreement		Quantitative disagreement		Categorical disagreement	
	1978-2009		1978-2009		2000-2009		2000-2009	
Lagged	0.789	(0.00)	0.871	(0.00)	0.673	(0.00)	0.835	(0.00)
Survey news	-0.035	(0.00)	-0.046	(0.03)	0.053	(0.58)	-0.127	(0.01)
Inflation	0.231	(0.00)	-0.045	(0.53)	-0.240	(0.04)	-0.061	(0.33)
Inflation^2	-0.057	(0.51)	0.052	(0.46)	0.300	(0.08)	0.087	(0.27)
$(\Delta\text{Inflation})^2$	0.014	(0.11)	0.130	(0.00)	0.102	(0.03)	0.180	(0.00)
obs.	383		383		120		120	
R^2	0.62		0.83		0.63		0.86	

Note: We report coefficient estimates that have been normalized by multiplying OLS coefficients with the standard deviation of the regressor and dividing by the standard deviation of the dependent variable. *P*-values derived from heteroskedasticity and auto-correlation robust standard errors (Newey-West) are reported in parentheses.

Table 2

Quantitative disagreement and public news

Sample: 1990-2009						
Lagged					0.833	(0.00)
Public news			0.272	(0.00)	0.031	(0.28)
Inflation	-0.081	(0.54)	-0.264	(0.06)	-0.008	(0.85)
Inflation^{2}2	0.504	(0.00)	0.627	(0.00)	0.099	(0.06)
$(\Delta\text{Inflation})^2$	-0.023	(0.67)	0.007	(0.89)	0.024	(0.21)
obs.	240		240		240	
R^2	0.19		0.25		0.78	
Sample: 2000-2009						
Lagged					0.664	(0.00)
Public news			-0.157	(0.19)	-0.086	(0.21)
Inflation	-0.922	(0.00)	-0.877	(0.00)	-0.233	(0.04)
Inflation^2	1.045	(0.00)	1.110	(0.00)	0.391	(0.02)
$(\Delta\text{Inflation})^2$	0.225	(0.00)	0.233	(0.00)	0.118	(0.01)
obs.	120		120		120	
R^2	0.33		0.34		0.63	

Note: We report coefficient estimates that have been normalized by multiplying OLS coefficients with the standard deviation of the regressor and dividing by the standard deviation of the dependent variable. *P*-values derived from heteroskedasticity and autocorrelation robust standard errors (Newey-West) are reported in parentheses.

Table 3

Categorical disagreement and public news

Sample: 1990-2009						
Lagged					0.866	(0.00)
Public news			-0.397	(0.00)	-0.043	(0.10)
Inflation	-0.807	(0.00)	-0.539	(0.01)	-0.048	(0.43)
Inflation^2	0.389	(0.10)	0.210	(0.32)	0.045	(0.51)
$(\Delta\text{Inflation})^2$	0.137	(0.02)	0.093	(0.13)	0.133	(0.00)
obs.	240		240		240	
R^2	0.27		0.41		0.83	
Sample: 2000-2009						
Lagged					0.838	(0.00)
Public news			-0.532	(0.00)	-0.082	(0.05)
Inflation	-0.573	(0.01)	-0.419	(0.05)	-0.027	(0.67)
Inflation^2	-0.101	(0.67)	0.121	(0.51)	0.021	(0.76)
$(\Delta\text{Inflation})^2$	0.143	(0.03)	0.171	(0.00)	0.168	(0.00)
obs.	120		120		120	
R^2	0.48		0.63		0.86	

Note: We report coefficient estimates that have been normalized by multiplying OLS coefficients with the standard deviation of the regressor and dividing by the standard deviation of the dependent variable. *P*-values derived from heteroskedasticity and autocorrelation robust standard errors (Newey-West) are reported in parentheses.

Table 4

Assessment of model properties

	Constant δ:			Time-varying δ:		
	SI	SE	EPI	SI	SE	EPI
Inflation expectations						
Jan 1978 - Jul 1987	0.867	0.834	.	0.893	0.857	.
Aug 1987 - Sep 2001	0.753	0.724	0.592	0.708	0.634	0.533
Oct 2001 - Dec 2009	0.561	0.580	0.298	0.611	0.635	0.120
Full sample	0.861	0.863	.	0.875	0.871	.
Quantitative disagreement						
Jan 1978 - Jul 1987	0.699	0.425	.	0.646	0.270	.
Aug 1987 - Sep 2001	0.120	0.203	0.219	0.135	0.226	0.254
Oct 2001 - Dec 2009	0.559	0.525	0.351	0.418	0.521	0.486
Full sample	0.522	0.486	.	0.475	0.443	.
Categorical disagreement						
Jan 1978 - Jul 1987	-0.404	0.378	.	-0.311	0.518	.
Aug 1987 - Sep 2001	0.269	0.242	0.297	0.278	0.252	0.301
Oct 2001 - Dec 2009	0.617	0.641	0.359	0.682	0.728	0.413
Full sample	0.241	0.435	.	0.336	0.516	.

Note: Reported are correlation coefficients between respective model-implied and survey-based variables. The three variants of the model are sticky information (SI), sticky expectations (SE) and epidemiology (EPI). The dots appear in the columns of the epidemiological model because the Survey of Professional Forecasters is available only after 1982.