Oxford Economic Papers, 67(3), 2015, 634–660
doi: 10.1093/oep/gpv003
Advance Access Publication Date: 11 February 2015

Expectation errors, uncertainty, and economic activity

By Yavuz Arslan[a], Aslıhan Atabek[a], Timur Hulagu[b], and Saygın Şahinöz[a]

[a]Central Bank of the Republic of Turkey
[b]Central Bank of the Republic of Turkey, Istiklal Cad. No. 10 Ulus, 06100 Ankara, Turkey; e-mail: timur.hulagu@tcmb.gov.tr

Abstract

In this article we analyse the relationship between uncertainty and economic activity. For this purpose, we use a firm-level panel data set from Turkey to form proxies for uncertainty by using expectation errors of firms about their production volumes. The identifying assumption is that the probability of making an expectation error increases when the uncertainty faced increases. An analysis of the downturn in 2008–2009 shows that 44% of the decline in industrial production can be attributed to increased uncertainty. Moreover, we show that if a firm faces higher uncertainty it is more likely that it defers its investment plans.

JEL classifications: D8, C43, C82, E22, E32

1. Introduction

In this article, we use a firm-level panel data set from Turkey to study the relationship between economic activity and uncertainty. First, we form a new measure of uncertainty for Turkey by constructing the expectation errors of firms, which we do by comparing their survey responses about expectations and realizations on their production volumes. Our identifying assumption is that the probability of a firm making an expectation error increases when the uncertainty faced by that firm increases. The cross-correlations between economic activity (industrial production) and the uncertainty measures that we form show that there is a strong negative correlation and that uncertainty leads economic activity by five months. Next we show that the effect of uncertainty on economic activity is large. A 1 standard deviation increase in aggregate uncertainty causes a 0.4% decrease in the industrial production index (IPI) on impact. If we take into account the prolonged effects, the decrease in IPI reaches 5.9% in a year. Moreover, an analysis of the downturn in 2008–2009 shows that about 44% of the decline in industrial production can be attributed to the increased uncertainty.

One contribution of our article is separating 'total uncertainty' into two components: 'idiosyncratic uncertainty' and 'aggregate uncertainty'. We first form firm-specific forecast errors and then define the total uncertainty measure as being the average of squared firm-specific errors. Idiosyncratic uncertainty, on the other hand, is the variance of expectation errors made across firms. One problem with this measure is that when all firms make the same expectation error, the idiosyncratic uncertainty measure implies zero uncertainty. Aggregate uncertainty is defined as the square of the average expectation errors made across firms. Consequently, the aggregate uncertainty measure signals high uncertainty if there is a high number of firms making similar expectation errors. In our analysis we show that the aggregate uncertainty measure has a more pronounced effect on industrial production.

Finally, we use the panel dimension of our data set to investigate the effects of aggregate and firm-specific uncertainties on investment decisions. Our results show that both aggregate and firm-specific uncertainties have negative effects on firms' investment plans.

Our article is related to two strands of literature. One of the strands questions how to measure uncertainty given that there is not a widely accepted method for doing so. We contribute to this strand by separating uncertainty into aggregate and idiosyncratic components. Another strand of the literature explores the quantitative importance of uncertainty in real variables. We provide estimates for Turkey and show that they are in line with the earlier literature.

In the literature, several measures of uncertainty have been proposed and used. Bloom *et al*. (2012) use the variance and dispersions of several variables at establishment, firm, and industry levels to measure uncertainty. Some studies, such as Leahy and Whited (1996) and Bloom (2009), use stock market volatility as a measure of uncertainty. Another widely used uncertainty measure is the variance of forecasters' expectations (Bachmann *et al*., 2013). Baker *et al*. (2013) use the frequency of news related to policy uncertainty to form a proxy of policy uncertainty, which they found to be related to real activity, such as investment and output.[1]

The way we construct our uncertainty measures is closely related to Bachmann *et al*. (2013). They use the forecast errors of firms as a proxy of uncertainty and compare it with the other measures they have developed using forecast dispersion. Although they confirm that there is a strong negative relationship between uncertainty and economic activity, they conclude that they do not see the 'wait-and-see' effect. The idiosyncratic uncertainty measure used in our article is the same as the measure used by Bachmann *et al*. (2013). In fact, we separate total uncertainty into aggregate and idiosyncratic components and observe that the aggregate uncertainty measure performs better in explaining dynamics in the economic activity.[2]

More recently, Jurado *et al*. (2013) develop a new measure of uncertainty by obtaining the common components of forecast errors for several macroeconomic time series by using econometric methods. Whilst the techniques are quite different, the measure that we use here is closely related to theirs, as both of them rely on forecast errors. In our method,

1 See Gilchrist and Zakrajšek (2012), Scotti (2013), and Orlik and Veldkamp (2014) and for some other possible methods.

2 The discrepancy between our findings and the findings of Bachmann *et al*. (2013) is potentially due to the fact that the dynamics of aggregate uncertainty is possibly more important (compared to idiosyncratic uncertainty) in Turkey compared with Germany.

we obtain forecast errors from the responses, whereas they obtain them using econometric techniques.

Whilst it is generally acknowledged that there is a relation between uncertainty and economic activity, until recently this relationship has not been explored in detail in the literature. Guiso and Parigi (1999) and Bloom *et al*. (2007) show that uncertainty weakens the response of investments to demand shocks. In an influential study, Bloom (2009) argues that in a partial equilibrium model, higher uncertainty can cause a recession as it leads firms to use wait-and-see strategies, which will cause a slowdown in economic activity. In an accompanying paper, using data from establishments, firms, industries, and macroeconomic variables, Bloom *et al*. (2012) provide evidence that uncertainty is counter-cyclical. They then build a theoretical general equilibrium model to study the effects of uncertainty on economic activity, confirming the earlier findings of Bloom (2009).

More recently, several studies have further explored the quantitative importance of uncertainty shocks. Christiano *et al*. (2013) show that business cycles in the USA can be largely attributed to uncertainty shocks. Leduc and Liu (2012) argue, using a quantitative model, that the unemployment rate would be 1 percentage point less if uncertainty was at the pre-crisis level. Shoag and Veuger (2014) report that unemployment would be 1.4 percentage points lower if uncertainty for all the states in the USA were at the level of the five lowest states. In a set-up in which there are price rigidity and counter-cyclical markups, Basu and Bundick (2012) find that when the central bank is constrained by the zero lower bound (as has been the case for the USA), it is plausible that about one-fourth of the drop in the US output would be attributed to higher uncertainty. For the UK, Denis and Kannan (2013) argue that uncertainty shocks account for about a quarter of the decline in industrial production. For the emerging markets, Fernández-Villaverde *et al*. (2011) show that interest rate uncertainty alone can be a significant driver of the business cycles in emerging countries. These papers all point out that in developed countries, the effects of uncertainty on economic activity are potentially large. Our article presents the first empirical estimates of the quantitative importance of uncertainty in an emerging country. Our findings are within the range of those of earlier publications on the subject that studies developed countries.

In addition to research that looks at the effects of uncertainty without specifying its explicit source, a new strand of the literature specifically explores the effects of policy uncertainty on economic activity. Mumtaz and Zanetti (2013) find that a rise in monetary policy uncertainty induces declines in output growth, inflation, and nominal interest rates. Johannsen (2014) provides evidence showing that when there is a zero lower bound problem, fiscal uncertainty shocks can have a large impact on the economy. Fernández-Villaverde *et al*. (2011) study the effects of fiscal uncertainty shocks in a stochastic environment. In our article, the uncertainty measures that we form are combinations of all sources of uncertainty. Hence we are not able to separate the uncertainty into its explicit sources.

Whilst there is a wide literature that accepts uncertainty shocks as exogenous drivers of business cycles, there is another strand that suggests a possible reverse mechanism. Bachmann and Moscarini (2011), Bachmann *et al*. (2013), and Bachmann and Bayer (2013) argue that uncertainty can endogenously increase during bad times. As a result, they claim that rather than uncertainty being a force behind business cycles, it may be a product of them. Our results, however, support the exogeneity view as uncertainty leads output by five months in our data.

The remainder of this article is organized as follows. In Section 2, we discuss a theoretical model that shows that as the uncertainty in an economy increases, expectation errors also increase. The next section introduces the data and methodology. Section 4 reports the results of the econometric tests and analysis. Section 5 investigates the effects of uncertainty on firm investment, and Section 6 concludes. In the Online Appendix, we compare the performance of other uncertainty measures proposed in the literature.

2. Model

We introduce our model and show that when uncertainty increases, expectation errors also increase. For this purpose, we use a dispersed information set-up similar to the ones used in Morris and Shin (2002) and Lorenzoni (2009, 2010).

The model economy is populated by a continuum of firms indexed by i, whose production growth can be written as

$$y_{i,t} - y_{i,t-1} = \theta_t + \zeta_{i,t} \tag{1}$$

where $y_{i,t}$ is the logarithm of production of firm i at time t. Production growth of a firm has two components: the aggregate component θ_t and the idiosyncratic component $\zeta_{i,t}$. Both processes are independent and identically distributed normal random variables with mean zero and respective variances σ_θ^2 and σ_ζ^2.[3] Moreover, these processes are independent from each other, that is, neither has any information on guessing the other. We assume that firms observe $\zeta_{i,t}$ at the beginning of the period t.[4] On the other hand, firms do not have perfect information on θ_t; rather, they receive two noisy signals about the aggregate component. One of the noisy signals is private information with the specification

$$x_{i,t} = \theta_t + \epsilon_{i,t} \tag{2}$$

where $\epsilon_{i,t}$ is independent and identically distributed (i.i.d.) normal with mean zero and variance σ_ϵ^2. The other signal can be observed publicly and has the form

$$s_t = \theta_t + e_t \tag{3}$$

where e_t is i.i.d. normal with mean zero and variance σ_e^2. Again, processes θ_t, $\zeta_{i,t}$, $\epsilon_{i,t}$, and e_t are independent across agents and across time. The two noisy signals are the sources of dispersed information in the model. The public noise shock e_t causes all the firms to underestimate or over-estimate the macro production innovation. The idiosyncratic noise shock $\epsilon_{i,t}$, on the other hand, causes dispersed information about the current state of the micro and macro productivities given s_t.[5]

3 We discuss the case of persistent θt in the Online Appendix. There, we assume that the persistence is time-varying, that it includes cases in which the aggregate state of the economy evolves as a Markov process between recessions and expansions, and that expansions are more persistent than recessions.

4 Under this assumption, the expectation error of a firm about its own production will be equal to the expectation error made regarding the aggregate component. In the absence of any noisy signal about the idiosyncratic component, this assumption is not crucial, and one can reach the same conclusions we derive later.

5 The public signal resembles news about the state of the economy which is publicly available. The other signal theorizes any development in the firm's own productivity.

On the basis of signals in the economy, firms form expectations about the aggregate component of their production growth. Expected aggregate production growth is

$$E[\theta_t|x_{i,t}, s_t] = \frac{\alpha s_t + \beta x_{i,t}}{\alpha + \beta} \tag{4}$$

where $\alpha = 1/\sigma_e^2$ and $\beta = 1/\sigma_\epsilon^2$ make precise the public and private information, respectively. Equation (4) suggests that firms give more weight to information with higher precision. Letting $\kappa_{i,t} = \frac{\alpha e_t + \beta \epsilon_{i,t}}{\alpha+\beta}$, the term on the right-hand side can be rewritten as

$$\frac{\alpha s_t + \beta x_{i,t}}{\alpha + \beta} = \theta_t + \kappa_{i,t} \tag{5}$$

where using normality and i.i.d. property, $\kappa_{i,t} \sim N(0, \frac{1}{\alpha+\beta})$.

To maintain compatibility with our data set, in which firms give qualitative responses about expectations and past realizations of their production volume, we assume that each firm reports whether they expect θ_t to be larger than some upper-bound $\overline{\theta}$, smaller than some lower-bound $\underline{\theta}$, or between $\overline{\theta}$ and $\underline{\theta}$.[6] Similarly, we assume that each firm reports one period later whether they observed θ_t larger than $\overline{\theta}$, smaller than $\underline{\theta}$, or between $\overline{\theta}$ and $\underline{\theta}$. Specifically, a firm reports $a(\theta_t)$ tomorrow and $a(E[\theta_t|x_{i,t}, s_t])$ today in the following sense:

$$a(\theta_t) = \begin{cases} 1, & \theta_t > \overline{\theta} \\ 0, & \underline{\theta} < \theta_t < \overline{\theta} \\ -1, & \theta_t < \underline{\theta} \end{cases} \tag{6}$$

$$a(E[\theta_t|x_{i,t}, s_t]) = \begin{cases} 1, & E[\theta_t|x_{i,t}, s_t] > \overline{\theta} \\ 0, & \underline{\theta} < E[\theta_t|x_{i,t}, s_t] < \overline{\theta} \\ -1, & E[\theta_t|x_{i,t}, s_t] < \underline{\theta} \end{cases} \tag{7}$$

If a firm's measured expectation $a(E[\theta_t|x_{i,t}, s_t])$ does not fit the measured realization $a(\theta_t)$, we name this as an expectation error. More rigorously, U denotes the square of the expectation error made by a firm, which can be written as

$$U(\theta_t) = [a(\theta_t) - a(E[\theta_t|x_{i,t}, s_t])]^2. \tag{8}$$

We now show that as uncertainty in the economy rises, the probability of firms making expectation errors also increases for any realization of θ_t.

Lemma 1 $\frac{\partial P(U(\theta_t)>0)}{\partial \sigma_e} > 0$ and $\frac{\partial P(U(\theta_t)>0)}{\partial \sigma_\epsilon} > 0$ for any θ_t unambiguously.

Proof There are only three cases where firms make no expectation error. Particularly, the following events will lead to $U = 0$:

i. $E[\theta_t|x_{i,t}, s_t] < \underline{\theta}$ given $\theta_t < \underline{\theta}$,
ii. $\underline{\theta} < E[\theta_t|x_{i,t}, s_t] < \overline{\theta}$ given $\underline{\theta} < \theta_t < \overline{\theta}$,
iii. $E[\theta_t|x_{i,t}, s_t] > \overline{\theta}$ given $\theta_t > \overline{\theta}$.

What we essentially show in this proof is that the probabilities of these events monotonically shrink as σ_e or σ_ϵ rise. Equivalently, it is enough to show that changes in

6 Bounds can be different for each firm.

α or β lead to changes in these probabilities in the same direction. To achieve this, we first define

$$Z_{i,t} = \kappa_{i,t}\sqrt{\alpha+\beta} \tag{9}$$

where using normality and i.i.d. property of $\kappa_{i,t}$, $Z_{i,t}$ is distributed i.i.d. as standard normal. Now, considering our first case,

$$\begin{aligned} P(E[\theta_t|x_{i,t},s_t] < \underline{\theta}) &= P(\theta_t + \kappa_{i,t} < \underline{\theta}) = P(\kappa_{i,t} < \underline{\theta} - \theta_t) \\ &= P(Z_{i,t} < \sqrt{\alpha+\beta}(\underline{\theta} - \theta_t)) \\ &= \Phi(\sqrt{\alpha+\beta}(\underline{\theta} - \theta_t)), \end{aligned} \tag{10}$$

where $\Phi(.)$ is the standard normal cumulative distribution function. Note that since $\theta_t < \underline{\theta}$ in the first case, the term inside the operator $\Phi(.)$ is positive and is increasing in α or β. Therefore, any decrease in precision (or equivalently, an increase in uncertainty) leads to a decrease in the success probability. Proceeding to the second case,

$$\begin{aligned} P(\underline{\theta} < E[\theta_t|x_{i,t},s_t] < \overline{\theta}) &= P(\underline{\theta} < \theta_t + \kappa_{i,t} < \overline{\theta}) = P(\underline{\theta} - \theta_t < \kappa_{i,t} < \overline{\theta} - \theta_t) \\ &= P(\sqrt{\alpha+\beta}(\underline{\theta} - \theta_t) < Z_{i,t} < \sqrt{\alpha+\beta}(\overline{\theta} - \theta_t)) \\ &= \Phi(\sqrt{\alpha+\beta}(\overline{\theta} - \theta_t)) - \Phi(\sqrt{\alpha+\beta}(\underline{\theta} - \theta_t)). \end{aligned} \tag{11}$$

There are two terms on the right-hand side. Using $\underline{\theta} < \theta_t < \overline{\theta}$, one can see that the first term has a positive operand and therefore is increasing in precision terms, which in turn leads to an increase in the first probability function. The second term, on the other hand has a negative operand and is decreasing in precision terms. This leads to a decrease in the second probability function and hence the sum of the two probabilities monotonically increase in α or β. This completes the proof.[7]

Finally, we consider the other direction of the relationship between uncertainty and expectation errors. In particular, an increase in the square of expectation errors may stem from two possible causes in our model: an increase in uncertainty and a level shock in θ_t. However, we show in Lemma 2 that the latter is uncorrelated with squared expectation errors, and thus that movements in the square of expectation errors can only be correlated with changes in uncertainty.

Lemma 2 Assuming $\overline{\theta} - E[\theta_t] = E[\theta_t] - \underline{\theta}$, θ_t and $U(\theta_t)$ are uncorrelated.

Proof The covariance between θ_t and $U(\theta_t)$ can be written as

$$Cov(\theta_t, U(\theta_t)) = E[\theta_t U(\theta_t)] - E[\theta_t]E[U(\theta_t)] \tag{12}$$

Since $E[\theta_t] = 0$,[8] eq. (12) simplifies to

$$Cov(\theta_t, U(\theta_t)) = E[\theta_t U(\theta_t)] \tag{13}$$

7 Note that the third case is analogous to the first one.

8 The mean zero assumption is not crucial for the results. The only assumption needed is that bounds are equidistant from the mean.

Now when we write possible values of $U(\theta_t)$,

$$U(\theta_t) = \begin{cases} 0, & \begin{cases} \theta_t < \underline{\theta} \text{ and } \kappa_{i,t} < \underline{\theta} - \theta_t \\ \underline{\theta} < \theta_t < \overline{\theta} \text{ and } \underline{\theta} - \theta_t < \kappa_{i,t} < \overline{\theta} - \theta_t \\ \theta_t > \overline{\theta} \text{ and } \kappa_{i,t} > \overline{\theta} - \theta_t \end{cases} \\ 1, & \begin{cases} \theta_t < \underline{\theta} \text{ and } \underline{\theta} - \theta_t < \kappa_{i,t} < \overline{\theta} - \theta_t \\ \underline{\theta} < \theta_t < \overline{\theta} \text{ and } \kappa_{i,t} < \underline{\theta} - \theta_t \\ \underline{\theta} < \theta_t < \overline{\theta} \text{ and } \kappa_{i,t} > \overline{\theta} - \theta_t \\ \theta_t > \overline{\theta} \text{ and } \underline{\theta} - \theta_t < \kappa_{i,t} < \overline{\theta} - \theta_t \end{cases} \\ 4, & \begin{cases} \theta_t < \underline{\theta} \text{ and } \kappa_{i,t} > \overline{\theta} - \theta_t \\ \theta_t > \overline{\theta} \text{ and } \kappa_{i,t} < \underline{\theta} - \theta_t \end{cases}, \end{cases} \tag{14}$$

one can easily see that if bounds $\underline{\theta}$ and $\overline{\theta}$ are equidistant from the mean of θ_t, then $U(\phi) = U(-\phi)$ for any given $\phi \in \mathbb{R}$, that is, $U(\theta_t)$ is symmetric with respect to θ_t. Therefore, $E[\theta_t U(\theta_t)] = 0$.

Lemma 2 tells us that unexpected movements in production growth θ_t cause expectation errors, but those movements θ_t do not have any correlation with the expectation errors. This is because errors are symmetric around expected θ_t. If we observe large expectation errors for some θ, we will observe large expectation errors for $-\theta$ as well. To illustrate this better, Fig. 1 depicts simulation results analysing how average squared expectation errors change for a fixed level of uncertainty.[9] As can be seen, errors are made most frequently when shocks are near the decision bounds, whilst almost zero errors are made near the tails. This is intuitive, as firms do not make expectation errors when big shocks hit the economy, because θ_t then dominates the signals. According to the simulation results, the correlation between the level of shocks and squared expectation errors is almost zero. On the other hand, Fig. 2, which illustrates the relationship between uncertainty and squared expectation errors for a fixed level of shocks, clearly shows that the main source of expectation errors is the uncertainty in the economy. A correlation of 0.924 is estimated in the simulation results.

Empirically, foregoing arguments would imply that if the main source of expectation errors was the unexpected movements in the production growth θ_t, we would not see any correlation between expectation errors and economic activity. We would see small errors during extreme boom-bust periods and large errors during moderate recessions and moderate booms. In the next sections, we show that this view is not supported with the Turkish data. In particular, we show that expectation errors are large before recessions (even larger before severe recessions), but this is not the case for booms. Hence we should observe a hike in squared expectation errors in cases of increased uncertainty in the economy.

9 We use $\underline{\theta} = -1$ and $\overline{\theta} = 1$. The total number of random draws is 10,000.

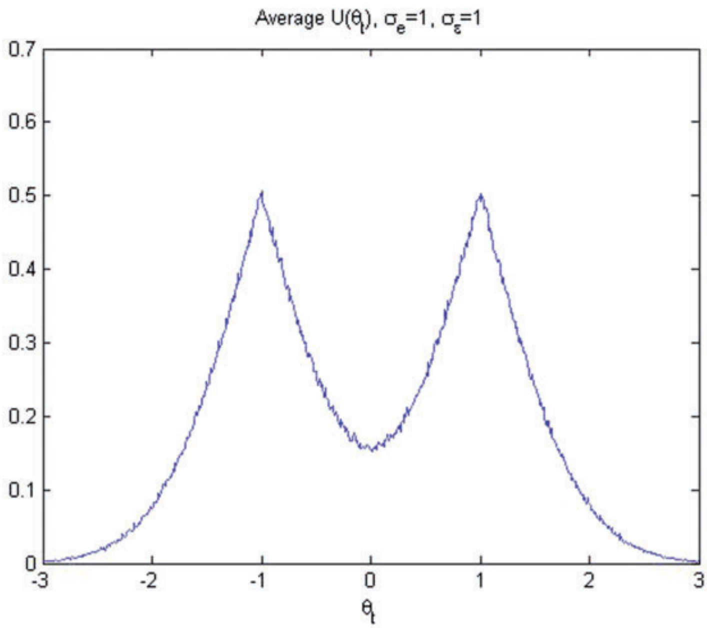


Fig. 1. Average squared expectation errors as a function of θ_t

Notes: Simulation results analysing how average squared expectation errors change for fixed level of uncertainty. We use $\underline{\theta} = -1$ and $\overline{\theta} = 1$. Total number of random draws is 10,000.

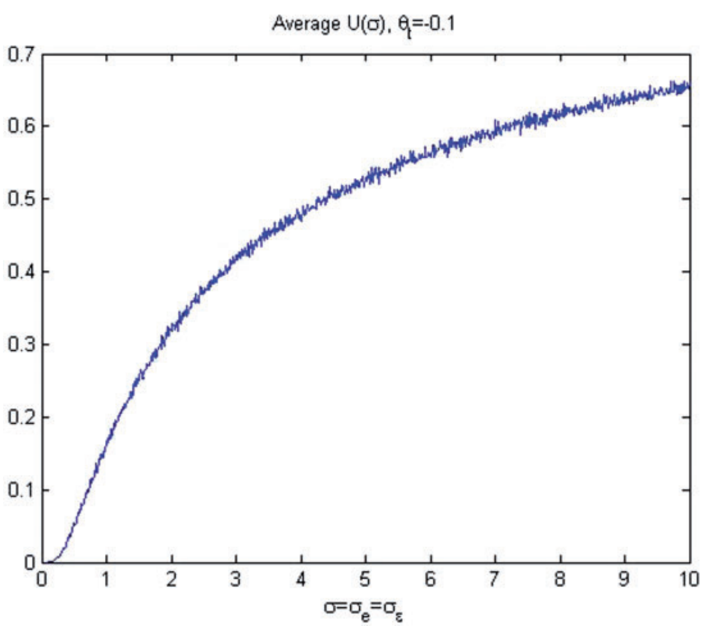


Fig. 2. Average squared expectation errors as a function of σ_e and σ_ϵ

Notes: Simulation results analysing the relationship between uncertainty and squared expectation errors for fixed level of shocks. Total number of random draws is 10,000.

3. Data and methodology

The Business Tendency Survey (BTS) is a monthly survey that has been conducted by the Central Bank of the Republic of Turkey (CBRT) since December 1987. It is aimed at producing indicators that will reflect the short-term tendencies in the manufacturing industry. The survey compiles the assessments of senior managers on the recent past, the current situation, and their expectations regarding future developments in the business environment. The scope of the survey involves several variables including production, sale orders, employment, inventories, prices, unit costs, producer prices inflation, interest rate on credits, and general trends in business conditions.

A major structural break occurred in this survey at the end of 2006. In particular, according to the Joint Harmonized EU Programme of Business and Consumer Surveys, a harmonization of the BTS with international standards and an improvement of the scope of the survey units had taken place by the end of 2006. Before 2006, the survey units were industrial firms listed in the Turkey's Top 500 Industrial Enterprises Survey and Turkey's Second 500 Industrial Enterprises Survey, published by the Istanbul Chamber of Industry. These firms were responsible for approximately 40% of total production in 2006. After the harmonization, the survey units were based on the Monthly Industrial Production Survey, which generated 90% of the total production value of private sector units with annual average of 20 or more employees in four-digit sectors of NACE Rev. 1.1.[10] With this harmonization study, a significant jump in the respondent size is observed. Specifically, the set of firm managers participating in the survey was on average four times greater after the harmonization period.[11]

In this article, we use expectation errors of firms concerning production volume to construct our uncertainty measures.[12] The idea of using expectation errors as a measure of uncertainty goes back to Bomberger (1996). There he decomposes by identity the (total) uncertainty about inflation expectations into two components: consensus uncertainty and disagreement. The former is the square of the deviation of average expectations from inflation realizations, whilst the latter is the square of the deviation of individual expectations from their average. Our methodology of constructing uncertainty measures follows the same idea.

To form our uncertainty measures, we use answers to the questions listed in Table 1 from the BTS. Question 5 asks about expectations for the next three months regarding firms' production, whilst question 1 asks about their realizations during the past three months. Therefore, answers to expectation questions at time t and realization questions at time $t+3$ cover the same period. As will be explained, this property allows us to analyse expectation errors.

10 The Statistical Classification of Economic Activities in the European Community (in French: Nomenclature statistique des activits conomiques dans la Communaut Europenne), commonly referred to as NACE, is a European industry standard classification system. Our data set does not allow us to control sectoral heterogeneity at the four-digit level of NACE 1.1. However, our results are robust when we control for them at the two-digit level.

11 Details of the survey can be found on the CBRT website: http://www.tcmb.gov.tr. Descriptive statistics for the total respondent sizes of the two periods are given in columns (2) and (3) of Table 1.

12 Questionnaire answers are subject to measurement errors. Moreover, the expectation error could be linked to level of manager expertise. However, these would not change our results unless measurement errors or manager expertise change during a business cycle.

Table 1. Questions

Question number	Question	Answer choices
Question 5	How do you expect your production to develop over the next 3 months? It will . . .	Increase, Remain unchanged, Decrease, No Answer
Question 1	How has your production developed over the past 3 months? It has . . .	Increased, Remained unchanged, Decreased, No Answer

Table 2. Summary statistics of monthly survey responses

	Whole sample		Paired sample		Matching rate (%)	
Statistic	Period 1	Period 2	Period 1	Period 2	Period 1	Period 2
Mean	343.8	1,465.3	266.7	1,233.2	78.4	85.7
Median	266.5	1,524	217.5	1,266.5	78.9	86.1
Minimum	199	962	151	789	67.0	80.2
Maximum	594	1978	465	1755	87.7	91.1
Standard deviation	126.0	267.3	90.9	241.0	4.1	3.0

Notes: Summary statistics of monthly survey respondent size are reported. Period 1 is the pre-harmonization period dating from 12/1987 to 12/2006 and period 2 is the post-harmonization, from 01/2007 to 09/2010. The first and second data columns represent summary statistics of all valid response counts of the monthly survey. The third and fourth data columns represent summary statistics of response counts which can be paired with a time $t+3$ survey such that expectation errors can be computed. The final two columns are summary statistics for the ratio of the paired sample over full sample.

To analyse the expectation errors, we first gathered the paired samples. In particular, firms with a valid answer at time t and $t+3$ formed our paired samples. Descriptive statistics of these paired samples through time are presented in columns (4) to (7) of Table 2.[13] Survey responses of the firms in these paired samples are used to derive forecast errors. Specifically, if the answer to the expectation question is different than the answer to the relevant realization question, this is called an expectation error and will be identified as an unexpected shock to the relevant variables. For example, a firm that expects an 'increase' in production (question 5) in January 2010 and responds to the realization (question 1) as 'decreased' in the April 2010 survey, then we can say that this firm made an expectation error in January 2010.

Our uncertainty measure is built on Bomberger (1996) and is an extension to the one used in Bachmann *et al*. (2013). The latter uses the root mean squared error (RMSE) measure on the expectation errors. Since we use qualitative survey data, it is necessary to

13 One can observe the differences in firm numbers of the paired samples for the two periods, and these differences might cause a break in the time series analysed. To investigate this possibility, we first applied the analysis only for the firms that participated in the pre-harmonization period, and then compared the results with the full-sample analysis. Although the firms that made up the two samples were selected with different criteria, results of the paper are robust to this structural break.

Table 3. Weights of expectation errors

		Development over the last 3 months ($t+3$)		
		Increased	Remained unchanged	Decreased
Expectations over the next 3 months (t)	Increase	0	−1/2	−1
	Remain unchanged	1/2	0	−1/2
	Decreased	1	1/2	0

employ some weights to quantify survey responses. Three possible answers[14] to each pair of questions construct a weight matrix for expectation errors as presented in Table 3. As an example, if a firm manager expects a 'decrease' and reports an 'increased' ('remained unchanged'), then that firm's uncertainty will be measured as 1 (1/2). The reason there are different figures for different answers is that as the realization departs further from the expectation, the uncertainty measure should reflect this accordingly.

Once Bachmann *et al*. (2013) obtain expectation errors, they introduce an uncertainty measure as the following:

$$Uncertainty_t^{Idiosyncratic} = \sum_{i=1}^{N} (W_{i,t} - \overline{W}_t)^2 / N \tag{15}$$

where

$$\overline{W}_t = \sum_{i=1}^{N} W_{i,t} / N \tag{16}$$

and $W_{i,t}$ is the weight of expectation error of firm i at time t, as introduced in Table 3.[15] We name this measure 'idiosyncratic uncertainty measure' because it measures how individual firms depart from the overall mean on expectation errors. However, we think that this measure is not sufficient for measuring uncertainty. For example, if all firms expect decreases in their production over the next three months at time t and observe a positive shock and report increases over the past three months at time $t+3$, then the idiosyncratic uncertainty will take on a value of 0. From this perspective, we study two more uncertainty measures: total and aggregate uncertainty measures, as introduced here.

$$Uncertainty_t^{Aggregate} = \overline{W}_t^2 \tag{17}$$

$$Uncertainty_t^{Total} = \sum_{i=1}^{N} (W_{i,t})^2 / N \tag{18}$$

Using eqs (15), (17), and (18), one can have the identity:

$$Uncertainty_t^{Total} = Uncertainty_t^{Idiosyncratic} + Uncertainty_t^{Aggregate} \tag{19}$$

14 We omit 'No Answer' responses for convenience. As a robustness check, those responses show no relation with economic activity.

15 We use $W_{i,t}^2$ as the firm-specific uncertainty measure in Section 5.

The aggregate uncertainty measure, $Uncertainty_t^{Aggregate}$, is the square of average expectation errors. Considering the foregoing example, the aggregate uncertainty measure will take on a value of 1, signalling a high uncertainty. At the other extreme, if the same proportion of firms make positive and negative expectation errors, hence cancelling each others' errors, this would mean an environment where firms face only idiosyncratic shocks. In this situation, the aggregate uncertainty will take on a value of 0, showing no aggregate shocks to the economy.

The total uncertainty measure, $Uncertainty_t^{Total}$, captures all expectation errors. This includes both the idiosyncratic and aggregate shocks that firms face. This identity is written in eq. (19).[16] In the next section, we analyse the relationships of each of these forms of uncertainty measures to economic activity.

4. Results

4.1 Cross-correlations and co-movement

We depict our uncertainty measures in terms of year-on-year changes in the IPI[17] in Fig. 3 as a measure of economic activity. As is apparent from this figure, idiosyncratic uncertainty follows a more stable path and is a measure that cannot capture economic downturns. Aggregate uncertainty, on the other hand, seems to be a good leading indicator of economic activity. One can observe that major spikes in the aggregate uncertainty measure are followed by troughs in economic activity.

As a next step, we report the cross-correlations of our uncertainty measures with several macroeconomic variables, namely, the IPI, investment, and firms' investment and employment expectations, in Table 4.[18] There are two important results that this analysis reveals. First, for each variable, there are strong negative correlations with our uncertainty measures (bold figures indicate the strongest absolute correlation amongst the lags). Moreover, one can see that uncertainty has a leading property with a two-to-five-month lag. Second, the results regarding the aggregate uncertainty measure are much stronger than the others, especially the idiosyncratic uncertainty, which is the one used by Bachmann *et al.* (2013).[19]

The first set of three rows of Table 4 show the relationship between IPI and the three uncertainty measures. Aggregate uncertainty leads IPI with a five-month lag and has a correlation of –0.51, which means that a higher uncertainty today signals a decrease in production in five months. Idiosyncratic uncertainty, on the other hand, leads IPI with a two-month lag and has a lower absolute correlation with IPI, of –0.29.

16 Bomberger (1996) considers a similar decomposition of total uncertainty about inflation. In his work, the three measures in eq. (19) are referred to respectively as total uncertainty, disagreement, and consensus uncertainty. The latter is computed very similarly except that survey participants report their expectations about an aggregate variable rather than their own production.

17 IPI is adjusted for calendar day effects. Atabek *et al.* (2009) provide evidence of the importance of calendar day effects on Turkish industrial production series.

18 A dynamic cross-correlation analysis for other uncertainty measures proposed in the literature is given in the Online Appendix.

19 At this point we should clarify that the difference between our findings and those of Bachmann *et al.* (2013) may be due to the different countries analysed. Both findings are consistent with the view that the aggregate uncertainty is a dominant factor of total uncertainty in Turkey, whilst it is not in Germany.

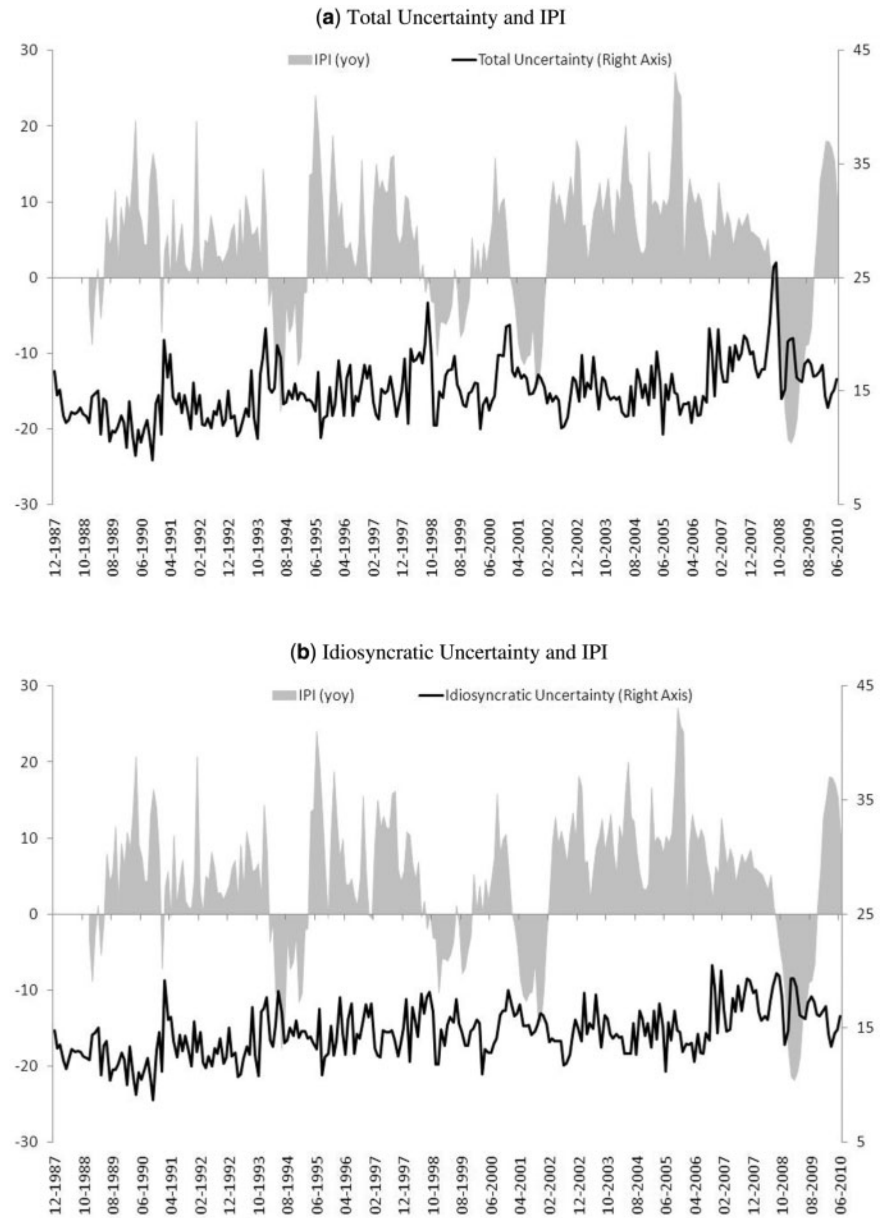


Fig. 3. Uncertainty measures and industrial production index (IPI_ (a) Total uncertainty and IPI (b) Idiosyncratic uncertainty and IPI (c) Aggregate uncertainty and IPI

Notes: Grey shaded areas represent year-on-year percentage changes in the iIPI, whereas solid lines depict our uncertainty measures.

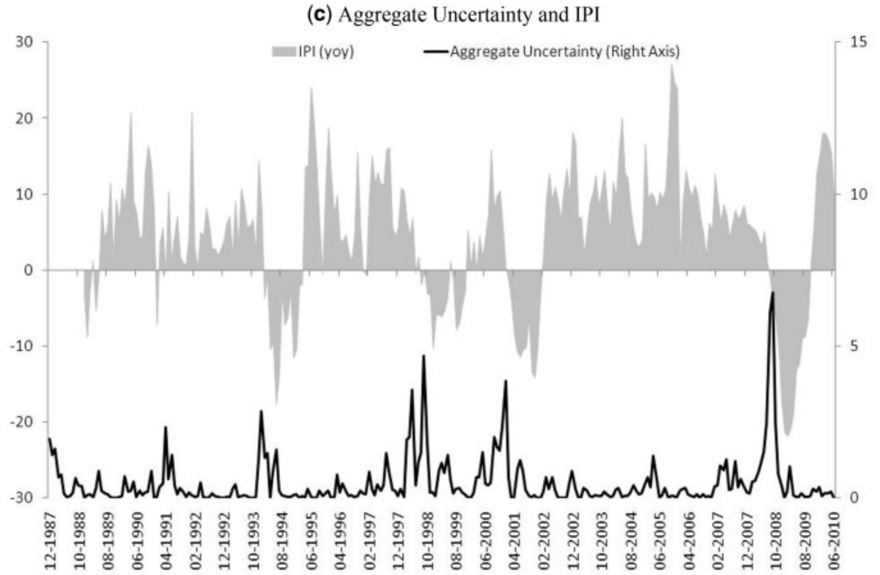


Fig. 3. Continued.

Next we use two different variables related to investment. The second set of three rows in Table 4 presents the cross-correlations of uncertainty measures with the first investment variable, the gross fixed capital formation component of GDP with constant prices. Since GDP data is quarterly, we employ quarterly averages of our uncertainty measures. According to the results, the relationship looks similar to that in the case of production. The main difference is the change in the lag structure. Particularly, aggregate uncertainty leads investment with a three-quarters lag (–0.54), whilst idiosyncratic uncertainty leads with a quarter lag (–0.37). The third set of three rows documents the cross-correlations of uncertainty measures with the second investment variable, investment expectations. Specifically we use the investment expectations of firms that we obtained from BTS balance results. The correlations are similar to the earlier ones of production and investment.

The last cross-correlation analysis that we perform is between BTS firms' employment expectations and uncertainty. Results in the bottom three rows of Table 4 further emphasize the relative importance of the aggregate uncertainty measure. In particular, idiosyncratic uncertainty shows no significant relationship between employment expectations and reduces the relationship of the total uncertainty measure due to aggregation. Aggregate uncertainty, on the other hand, has a strong negative and leading relationship with employment expectations.

Figure 4 depicts the aggregate uncertainty measure with investment (year-on-year change), investment expectations, and employment expectations, respectively. All three sub-figures are in line with the aforementioned evidence on the leading and negative relationships between the aggregate uncertainty measure and economic activity measures.[20]

20 We further employed a Granger causality test to investigate causal relationships between different uncertainty measures (aggregate, idiosyncratic, and total uncertainty) and economic variables (IPI, investment, and expectations of investment and employment). Results, which are available

Table 4. Cross-correlations of uncertainty measures with economic activity

		$t-6$	$t-5$	$t-4$	$t-3$	$t-2$	$t-1$	t	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$	$t+6$
IPI_t	$Uncertainty_t^{Total}$	−0.02	−0.04	−0.09	−0.13	−0.17	−0.21	−0.24	−0.25	−0.33	−0.36	−0.36	**−0.40**	−0.39
	$Uncertainty_t^{Idio.}$	−0.05	−0.07	−0.12	−0.16	−0.19	−0.24	−0.25	−0.23	**−0.29**	−0.28	−0.25	−0.28	−0.27
	$Uncertainty_t^{Agg.}$	0.07	0.05	0.03	0.01	−0.02	−0.05	−0.11	−0.18	−0.27	−0.39	−0.45	**−0.51**	−0.50
I_t^*	$Uncertainty_t^{Total}$	−0.01	0.04	0.12	0.15	0.08	−0.11	−0.30	−0.42	**−0.46**	−0.40	−0.25	−0.17	−0.10
	$Uncertainty_t^{Idio.}$	0.02	0.06	0.12	0.13	0.04	−0.14	−0.30	**−0.37**	−0.35	−0.27	−0.13	−0.10	−0.10
	$Uncertainty_t^{Agg.}$	−0.07	−0.03	0.06	0.13	0.15	0.02	−0.17	−0.37	−0.52	**−0.54**	−0.44	−0.27	−0.05
Ψ_t	$Uncertainty_t^{Total}$	0.14	0.10	0.05	0.01	−0.02	−0.05	−0.08	−0.13	−0.20	−0.24	−0.25	**−0.26**	−0.24
	$Uncertainty_t^{Idio.}$	0.12	0.08	0.03	0.00	−0.04	−0.05	−0.06	−0.08	−0.11	−0.11	−0.12	**−0.13**	−0.11
	$Uncertainty_t^{Agg.}$	0.14	0.11	0.09	0.05	0.03	−0.02	−0.08	−0.20	−0.33	−0.43	−0.46	**−0.46**	−0.46
Ω_t	$Uncertainty_t^{Total}$	0.16	0.12	0.07	0.03	−0.01	−0.06	−0.06	−0.11	−0.17	**−0.20**	−0.19	−0.15	−0.09
	$Uncertainty_t^{Idio.}$	0.13	0.10	0.06	0.03	−0.02	−0.07	−0.04	−0.03	−0.04	−0.04	−0.02	0.00	0.05
	$Uncertainty_t^{Agg.}$	0.15	0.11	0.07	0.04	0.02	−0.01	−0.08	−0.24	−0.42	**−0.52**	−0.52	−0.47	−0.41

Notes: Variables are defined as follows. IPI_t: Industrial production index, adjusted for calendar day effects, year-on-year change, source TURKSTAT. I_t: Investment component of GDP, constant prices, year-on-year change, source TURKSTAT. Ψ_t: Firms' 12-month expectations of own investment, balance from BTS data, source CBRT. Ω_t: Firms' three-month expectations of own employment, balance from BTS data, source CBRT. Number of observations used for calculating cross-correlations between uncertainty measures and IPI_t, I_t, Ψ_t, and Ω_t are 259, 90, 271, and 271, respectively. Because investment data are quarterly, we used quarterly averages of uncertainty measures.

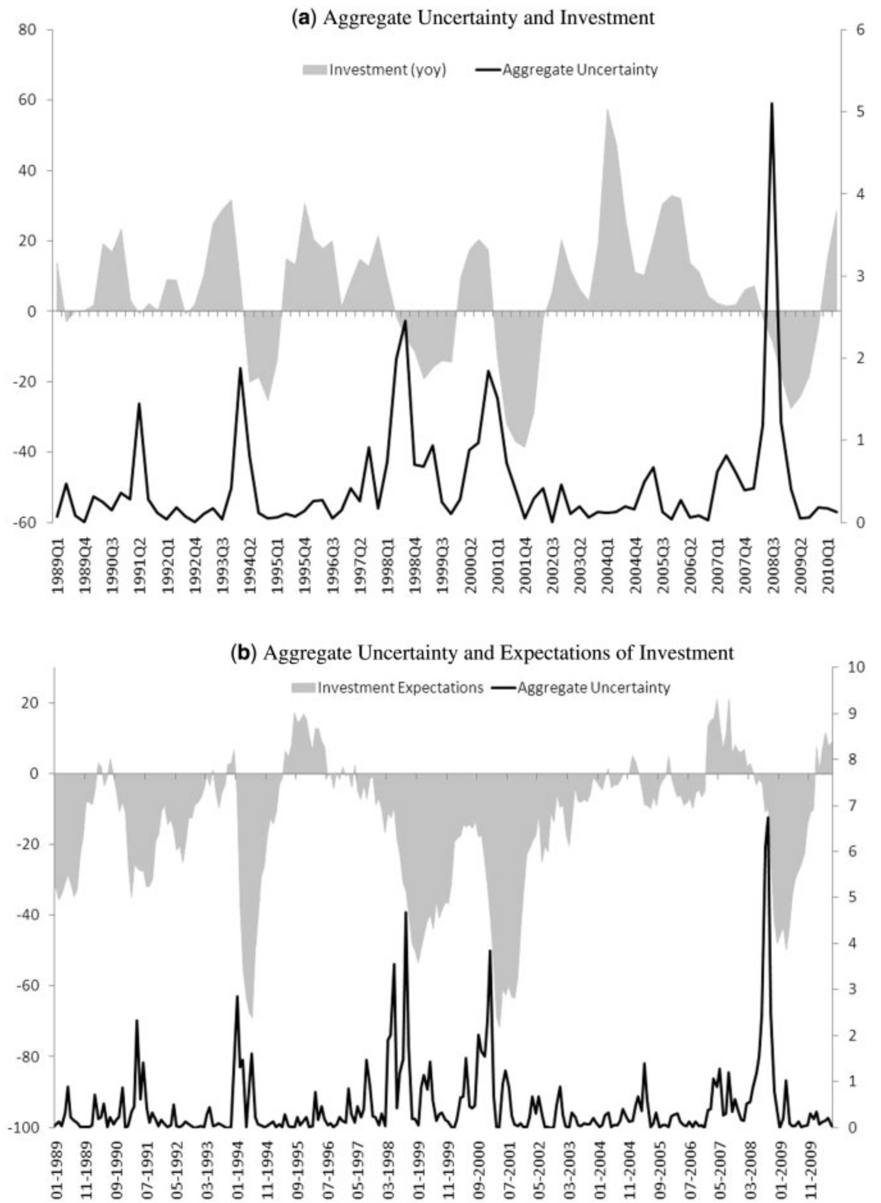


Fig. 4. Aggregate uncertainty measure and other economic activity variables
(a) Aggregate uncertainty and investment
(b) Aggregate uncertainty and expectations of investment
(c) Aggregate uncertainty and expectations of employment

Notes: Grey shaded areas represent year-on-year percentage changes in investment (gross fixed capital formation of GDP with constant prices), investment and employment expectations, whereas solid lines depict our aggregate uncertainty measure and are scaled on the right axis. Expectations are derived from BTS using balance values of responses to related questions.

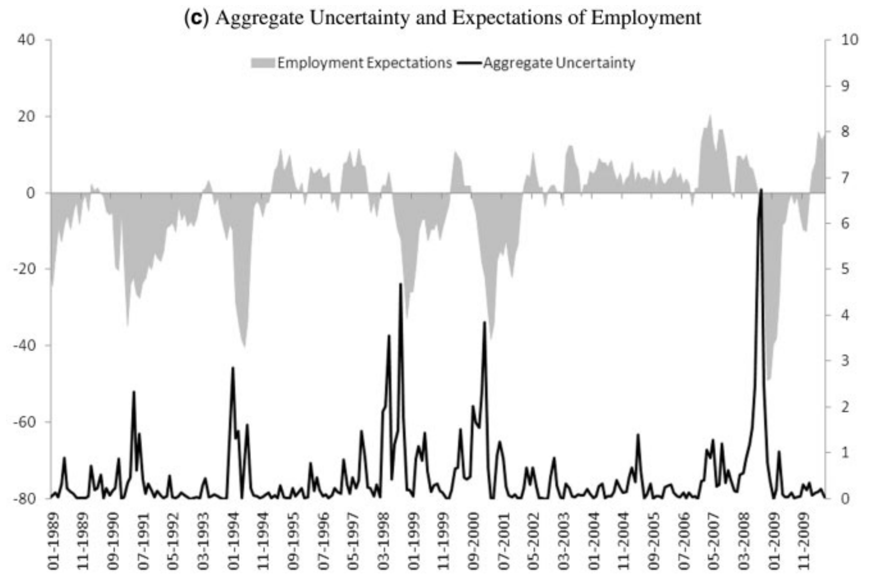


Fig. 4. Continued.

4.2 Regression results

We estimate the following specification to estimate the effect of uncertainty on economic activity:

$$y_t = \alpha + \sum_{i=1}^{5} \rho_i y_{t-i} + \beta X_{t-j} + \theta \epsilon_{t-12} + \epsilon_t \tag{20}$$

where y_t is year-on-year change of IPI after calendar day adjustment. To remove the heteroscedastic variance of the error term, ϵ_t, a GARCH(1,2) model is estimated for the conditional variance:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \beta_2 \sigma_{t-2}^2 \tag{21}$$

To analyse the effects of uncertainty on industrial production, we feed uncertainty measures to the regression equation one by one. X_{t-j} is the uncertainty measure, where j is the appropriate lag. We further control for the level effects by using the mean expectations of participants about their production volume.[21] Table 5 shows the estimation results for different specifications.[22] The first column has ARMA with GARCH model estimates, which we use as a benchmark case.[23] As one can see in other columns, all coefficients of uncertainty

on request, reveal a unidirectional causality from uncertainty to economic activity for all uncertainty measures.

21 Economic activity may show different behaviour during contractions and expansions in terms of duration and strength (see, for example, McKay and Reis, 2008). In an earlier study on the Turkish economy, Atabek *et al.* (2005) show that slowdowns are generally sharper and longer than expansions. Because of this fact, the predictive powers of our uncertainty measures could be the result of the briskness of recessions vis-à-vis booms. To take this into account, we control for level effects.

22 Estimation results for the pre-harmonization period are given in Table 6 for comparison.

23 We use the Schwarz information criterion to determine the proper model.

Table 5. Economic activity and uncertainty

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
IPI_{t-1}	0.83	0.84	0.79	0.84	0.80	0.77	0.78
	(0.06)***	(0.06)***	(0.07)***	(0.06)***	(0.06)***	(0.06)***	(0.06)***
IPI_{t-2}	−0.08	−0.08	−0.10	−0.07	−0.10	−0.05	−0.05
	(0.08)	(0.08)	(0.09)	(0.08)	(0.09)	(0.08)	(0.08)
IPI_{t-3}	0.04	0.02	0.09	0.01	0.09	0.03	0.03
	(0.08)	(0.07)	(0.09)	(0.07)	(0.08)	(0.07)	(0.08)
IPI_{t-4}	−0.01	0.00	−0.05	0.00	−0.05	0.01	0.01
	(0.07)	(0.07)	(0.08)	(0.07)	(0.07)	(0.06)	(0.07)
IPI_{t-5}	0.15	0.13	0.16	0.13	0.17	0.13	0.15
	(0.05)***	(0.05)**	(0.05)***	(0.05)***	(0.05)***	(0.05)**	(0.05)***
Level effects			4.05		4.02		2.23
			(1.06)***		(1.00)***		(1.07)**
$Uncertainty^{Total}_{t-2}$		−0.13	−0.21				
		(0.05)**	(0.06)***				
$Uncertainty^{Idio.}_{t-2}$				−0.15	−0.19		
				(0.06)**	(0.06)***		
$Uncertainty^{Agg.}_{t-5}$						−0.64	−0.47
						(0.21)***	(0.21)**
$ARCH(1)$	0.04	0.04	0.13	0.04	0.07	0.06	0.03
	(0.01)***	(0.01)***	(0.06)***	(0.01)***	(0.02)***	(0.02)***	(0.01)***
$GARCH(1)$	1.61	1.64	1.20	1.64	1.42	1.55	1.62
	(0.03)***	(0.03)***	(0.11)***	(0.03)***	(0.05)***	(0.06)***	(0.02)***
$GARCH(2)$	−0.94	−0.97	−0.69	−0.98	−0.90	−0.86	−0.96
	(0.03)***	(0.02)***	(0.13)***	(0.02)***	(0.06)***	(0.06)***	(0.02)***

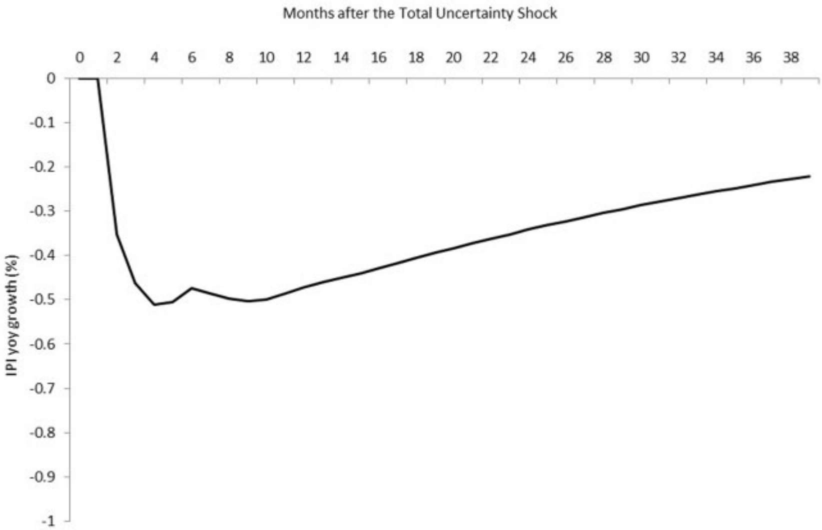
Notes: Dependent variable is the Industrial Production Index, adjusted for calendar day effects, year-on-year changes. Specifications are selected according to Schwarz information criterion. Season fixed effects and MA terms are included in all specifications. The numbers in parentheses are standard errors; *, **, and *** denote significance at 10%, 5%, and 1%, respectively. The variable 'level effects' is the mean expectations of participants about their production volume. Number of observations used in estimation is 254.

measures are negative and significant when we do and when we do not control for the level effects. Findings suggest that total and idiosyncratic uncertainty measures lead IPI growth by two months, whereas aggregate uncertainty leads by five months. This lead structure is similar to the results of the VAR analysis by Bloom (2009). In addition, the aggregate uncertainty has the highest significance amongst all three measures.

To quantify the adverse effects of uncertainty shocks on economic activity, we calculate impulse response functions[24] and draw them in Fig. 5. As can be seen from the figure, aggregate uncertainty shock has the highest impact on industrial production. A 1 standard deviation of aggregate uncertainty shock causes a 0.4% decline in the growth rate of industrial production after five months. If we consider the prolonged effects of the shock, the model implies a 5.9% decline within a year. We should note that a high persistence of the IPI ($AR(1)$ coefficient equals to 0.81) plays an important role in the size of this effect.

24 We first fit AR models to our uncertainty measures. Results are presented in Table 7. Then, by feeding 1 standard deviation shocks to the specifications in columns (2), (4), and (6) in Table 5, we obtain impulse response functions.

(a) Total Uncertainty and IPI



(b) Idiosyncratic Uncertainty and IPI

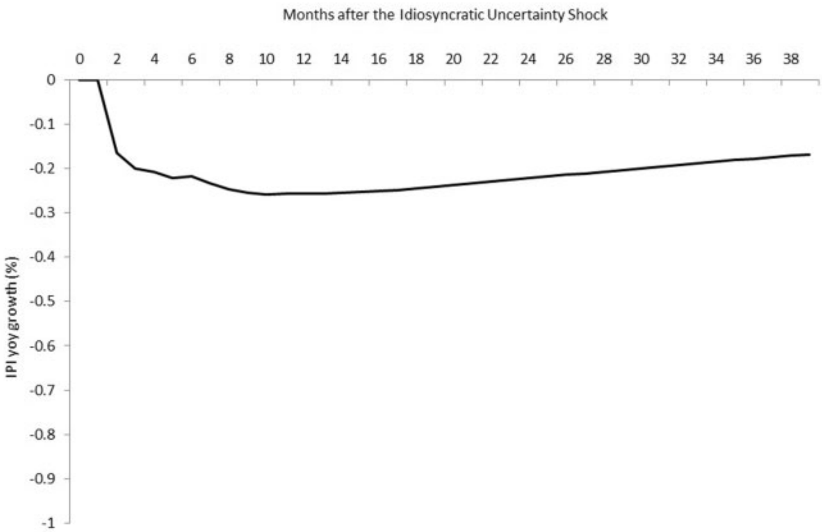


Fig. 5. Impulse responses of IPI to 1 standard deviation uncertainty shocks
(a) Total uncertainty and IPI
(b) Idiosyncratic uncertainty and IPI
(c) Aggregate uncertainty and IPI
Notes: To obtain impulse response figures, we feed 1 standard deviation shocks to the specifications in columns (2), (4) and (6) in Table 5.

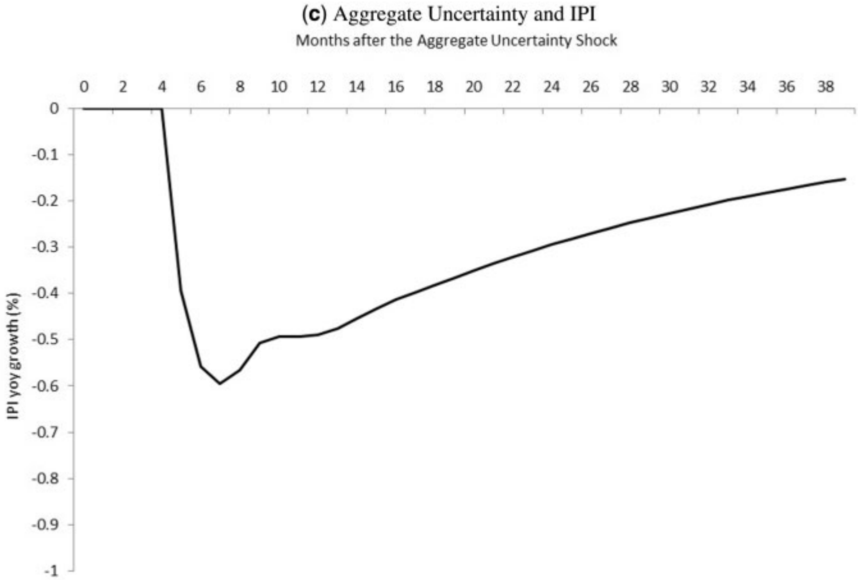


Fig. 5. Continued.

Next we perform an analysis of the recent downturn in the 2008–2009 period. A 21.8% annual decline in IPI was observed during this downturn. All three measures had increased by more than 2 standard deviations six months before the recession. First, we compute respective uncertainty shocks by using residuals from the models given in Table 7. Then, we calculate cumulative impacts of those shocks by using the impulse response functions described above. Results show that about 44% of the decline within a year in industrial production can be attributed to the increased uncertainty. We further show that of this 44%, 60% comes from aggregate uncertainty, whilst 40% is from idiosyncratic uncertainty.

5. Investment under uncertainty: an ordered probit analysis

Having analysed the relationship between uncertainty and macroeconomic activity, we now perform a micro-level analysis instead. In particular, we use the panel dimension of our data set to study the effect of uncertainty on firms' investment decisions. Employing our main intuition regarding expectation errors and uncertainty, we test the hypothesis that if a firm faces higher uncertainty, it will defer its investment plans. Thus, we estimate an ordered probit model with random effects to investigate the impact of uncertainty on investment decisions. Specifically, we use the aggregate uncertainty, $Uncertainty_t^{Aggregate}$, and firm-specific uncertainty, W_{it}^2 (square of firm i expectation errors at time t), as specified in the methodology section.

The BTS provides qualitative information on firms' expectations about their own future investment, demand, and production changes, on the basis of which we construct investment, demand, and production measures. Our measures of these are based on the answers to the questions in Table 8.

Table 6. Economic activity and uncertainty (pre-2007 period)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
IPI_{t-1}	0.77	0.78	0.73	0.79	0.72	0.77	0.65
	(0.06)***	(0.06)***	(0.06)***	(0.07)***	(0.05)***	(0.06)***	(0.06)***
IPI_{t-2}	−0.01	−0.05	0.01	−0.03	−0.01	−0.02	0.05
	(0.08)	(0.09)	(0.07)	(0.08)	(0.08)	(0.09)	(0.07)
IPI_{t-3}	−0.00	0.04	−0.06	0.00	0.00	0.00	−0.04
	(0.08)	(0.08)	(0.07)	(0.07)	(0.07)	(0.08)	(0.07)
IPI_{t-4}	0.01	0.02	0.09	0.02	0.04	0.01	0.04
	(0.08)	(0.07)	(0.05)	(0.07)	(0.06)	(0.07)	(0.06)
IPI_{t-5}	0.14	0.12	0.18	0.12	0.19	0.13	0.15
	(0.06)**	(0.06)**	(0.04)***	(0.06)**	(0.04)***	(0.06)**	(0.05)***
Level effects			6.14		6.26		5.98
			(1.25)***		(1.33)***		(1.36)***
$Uncertainty^{Total}_{t-2}$		−0.14	−0.15				
		(0.07)**	(0.06)**				
$Uncertainty^{Idio.}_{t-2}$				−0.11	−0.19		
				(0.08)	(0.07)***		
$Uncertainty^{Agg.}_{t-5}$						−0.58	−0.45
						(0.24)**	(0.22)**
$ARCH(1)$	0.07	0.07	0.04	0.07	0.02	0.08	0.04
	(0.02)***	(0.02)***	(0.01)***	(0.02)***	(0.01)**	(0.03)***	(0.01)***
$GARCH(1)$	1.58	1.64	1.65	1.59	1.67	1.53	1.64
	(0.05)***	(0.05)***	(0.02)***	(0.05)***	(0.01)***	(0.08)***	(0.02)***
$GARCH(2)$	−0.88	−0.87	−1.01	−0.88	−1.01	−0.85	−0.99
	(0.04)***	(0.05)***	(0.01)***	(0.04)***	(0.01)***	(0.07)***	(0.01)***

Notes: Dependent variable is the Industrial Production Index, adjusted for calendar day effects, year-on-year changes. Specifications are selected according to Schwarz information criterion. Season fixed effects and MA terms are included in all specifications. The numbers in parentheses are standard errors; *, **, and *** denote significance at 10%, 5%, and 1%, respectively. The variable 'level effects' is the mean expectations of participants about their production volume. Number of observations used in estimation is 212 because data from December 1987 to December 2006 are used.

Table 7. Autoregressive properties of uncertainty measures

y_t	$Uncertainty^{Total}$	$Uncertainty^{Idio.}$	$Uncertainty^{Agg.}$
y_{t-1}	0.53	0.41	0.63
	(0.06)***	(0.06)***	(0.05)***
y_{t-2}	0.14	0.13	
	(0.06)**	(0.07)**	
y_{t-3}		0.16	
		(0.06)***	
Constant	5.00	4.36	0.17
	(0.81)***	(0.89)***	(0.05)***
No. of observations	269	268	270
R^2	0.39	0.35	0.40

Notes: Specifications are selected according to Schwarz information criterion. The numbers in parentheses are standard errors; *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

Table 8. Questions

	Question	Answer choices
Question 5	How do you expect your production to develop over the next 3 months? It will …	Increase, Remain unchanged, Decrease, No answer
Question 17	How do you expect your overall orders to develop over the next 3 months? It will …	Increase, Remain unchanged, Decrease, No answer
Question 23	Compared to the last 12 months, how do you expect your fixed investment expenditure to change over the next 12 months? It will …	Increase, Remain unchanged, Decrease, No answer

We create categorically ordered indicator variables I_{it}, d_{it}, s_{it} for each firm that denote whether the investment, demand, and production expectations of the firm increase, remain unchanged, or decrease at time t. The indicator variables attain values of -1, 0, and 1, respectively. It is assumed that the investment expectation of a firm i at time t, I_{it}, depends on the commercial credit interest rate,[25] i_t^c, its expectation about firm-specific demand, d_{it}, its expectation about firm-specific production, s_{it}, its idiosyncratic uncertainty, W_{it}^2, and the aggregate uncertainty of the economy, $Uncertainty_t^{Aggregate}$, as well as some lags of these variables according to the conditional linear model. We use d_{it} and s_{it} to control for the level effects.[26] In particular, we employ the model:

$$\begin{aligned} I_{it}^* = & \sum_{j=0}^{12} \beta_{1j} W_{it-j}^2 + \sum_{j=0}^{12} \beta_{2j} Uncertainty_{t-j}^{Aggregate} \\ & + \sum_{j=0}^{12} \beta_{3j} d_{it-j} + \sum_{j=0}^{12} \beta_{4j} s_{it-j} + \beta_5 i_t^c + \varepsilon_{it}, \end{aligned} \quad (22)$$

where ε_{it} is a normally distributed random error with mean 0 and variance σ_ε, capturing unmeasured and unobservable effects on investment changes. Since the actual investment growth is a latent variable that is not directly observable, the expected investment growth I_{it} is assumed to be related to the latent investment variable I_{it}^* in the following manner.

$$I_{it} = \begin{cases} 1, & I_{it}^* > \mu_2 \\ 0, & \mu_1 < I_{it}^* < \mu_2 \\ -1, & I_{it}^* < \mu_1 \end{cases} \quad (23)$$

where μ_1 and μ_2 represent thresholds to be estimated along with the parameters $\beta_{1j}, \beta_{2j}, \beta_{3j}$, and β_{4j}. For identification purposes, we set $\sigma_\varepsilon = 1$. Given the assumption that the error

25 The commercial credit interest rate is the weighted average interest rate of the banking sector, which is calculated by weighting each bank's weighted and compounded average interest rates relating to its weekly amounts.

26 We also control for panel fixed effects and monthly seasonality.

Table 9. Ordered probit estimation results

	Coefficient	p-value
W_{it}^2	−0.04	0.03
$Unc._{t-5}^{Aggregate}$	−0.14	0.00
d_{it}	0.17	0.00
s_{it}	0.24	0.00
i_t^c	−0.17	0.00
μ_1	−0.70	0.00
μ_2	0.77	0.00
Number of observations	73,871	

Notes: Generalized Linear Latent And Mixed Models Stata package (*gllamm*) with adaptive quadrature option is used in the estimation. Due to the non-linearity of the ordered probit model, the estimated parameters cannot be interpreted as marginal effects. Thus, one can only interpret the sign of the effects, not the magnitudes. Firm fixed effects are controlled whilst 11 dummy variables representing months are used to control for seasonality. The insignificant coefficients of other lags of $Unc.^{Aggregate}$ are not reported.

term is normally distributed, the probabilities associated with the coded responses of the model are calculated as follows:

$$\begin{aligned} Pr(I_{it} = -1) = Pr(I_{it}^* < \mu_1) &= Pr\left(\sum_{j=0}^{12}\beta_{1j}W_{it-j}^2 + \sum_{j=0}^{12}\beta_{2j}Uncertainty_{t-j}^{Aggregate}\right. \\ &\quad \left. + \sum_{j=0}^{12}\beta_{3j}d_{it-j} + \sum_{j=0}^{12}\beta_{4j}s_{it-j} + \beta_5 i_t^c + \varepsilon_{it} < \mu_1\right) \\ &= \Phi\left(\mu_1 - \sum_{j=0}^{12}\beta_{1j}W_{it-j}^2 - \sum_{j=0}^{12}\beta_{2j}Uncertainty_{t-j}^{Aggregate}\right. \\ &\quad \left. - \sum_{j=0}^{12}\beta_{3j}d_{it-j} - \sum_{j=0}^{12}\beta_{4j}s_{it-j} - \beta_5 i_t^c\right) \end{aligned} \tag{24}$$

where $Pr(I_{it} = k)$ is the probability that firm i responds in manner k, and $\Phi(.)$ is the standard normal cumulative distribution function.[27]

The estimation results for the ordered probit model are reported in Table 9. Due to the non-linearity of the ordered probit model, the estimated parameters cannot be interpreted as marginal effects. Thus, from the estimation results, we can only interpret the sign of the effects, not the magnitudes. Table 9 suggests that both aggregate and firm-specific uncertainties have a negative effect on investment plans, as theory predicts. It is also important to note that the fifth lag of aggregate uncertainty is significant. This result appears to be reasonable given the potential time lag between uncertainty perception and investment decision.

To analyse the extent of the impact of demand and production expectations and aggregate and firm-specific uncertainty on investment decisions, we calculate the probabilities

27 Other probability values $Pr(I_{it} = 0)$ and $Pr(I_{it} = 1)$ can be computed in a similar fashion.

Table 10. Estimated probabilities from ordered probit model

$Pr(I_{it}=1\vert W_{it}^2=0, Unc._{t-5}^{Agg.}=0, d_{it}=1, s_{it}=1)$	**0.37**
$Pr(I_{it}=1\vert W_{it}^2=\sigma^W, Unc._{t-5}^{Agg.}=0, d_{it}=1, s_{it}=1)$	0.36
$Pr(I_{it}=1\vert W_{it}^2=0, Unc._{t-5}^{Agg.}=\sigma^A, d_{it}=1, s_{it}=1)$	0.30
$Pr(I_{it}=1\vert W_{it}^2=\sigma^W, Unc._{t-5}^{Agg.}=\sigma^A, d_{it}=1, s_{it}=1)$	0.30
$Pr(I_{it}=-1\vert W_{it}^2=0, Unc._{t-5}^{Agg.}=0, d_{it}=1, s_{it}=1)$	0.13
$Pr(I_{it}=-1\vert W_{it}^2=\sigma^W, Unc._{t-5}^{Agg.}=0, d_{it}=1, s_{it}=1)$	0.14
$Pr(I_{it}=-1\vert W_{it}^2=0, Unc._{t-5}^{Agg.}=\sigma^A, d_{it}=1, s_{it}=1)$	0.17
$Pr(I_{it}=-1\vert W_{it}^2=\sigma^W, Unc._{t-5}^{Agg.}=\sigma^A, d_{it}=1, s_{it}=1)$	0.18
$Pr(I_{it}=1\vert W_{it}^2=0, Unc._{t-5}^{Agg.}=0, d_{it}=-1, s_{it}=-1)$	0.12
$Pr(I_{it}=1\vert W_{it}^2=\sigma^W, Unc._{t-5}^{Agg.}=0, d_{it}=-1, s_{it}=-1)$	0.11
$Pr(I_{it}=1\vert W_{it}^2=0, Unc._{t-5}^{Agg.}=\sigma^A, d_{it}=-1, s_{it}=-1)$	0.10
$Pr(I_{it}=1\vert W_{it}^2=\sigma^W, Unc._{t-5}^{Agg.}=\sigma^A, d_{it}=-1, s_{it}=-1)$	0.09
$Pr(I_{it}=-1\vert W_{it}^2=0, Unc._{t-5}^{Agg.}=0, d_{it}=-1, s_{it}=-1)$	0.39
$Pr(I_{it}=-1\vert W_{it}^2=\sigma^W, Unc._{t-5}^{Agg.}=0, d_{it}=-1, s_{it}=-1)$	0.40
$Pr(I_{it}=-1\vert W_{it}^2=0, Unc._{t-5}^{Agg.}=\sigma^A, d_{it}=-1, s_{it}=-1)$	0.45
$Pr(I_{it}=-1\vert W_{it}^2=\sigma^W, Unc._{t-5}^{Agg.}=\sigma^A, d_{it}=-1, s_{it}=-1)$	0.46

Notes: Generalized Linear Latent And Mixed Models Stata package (*gllamm*) with adaptive quadrature option is used in the estimation. Expected probabilities with respect to the posterior distribution of the latent variables, which are computed by *gllapred* command with *mu* option, are shown. σ^W and σ^A represent 1 standard deviation shocks to W_{it}^2 and $Unc.^{Agg.}$, respectively.

for different possible values for d_{it}, s_{it}, W_{it}^2, and $Uncertainty_t^{Aggregate}$. The calculated probabilities are reported in Table 10. It follows from this table that there are asymmetries in the investment decision to aggregate and idiosyncratic uncertainty changes. Under positive demand and supply conditions, a 1 standard deviation increase in the firm-specific uncertainty decreases the probability of making a new investment decision only 1%. Under the same conditions, a similar increase in the aggregate uncertainty decreases the probability of making a new investment decision from 37% to 30%, and increases the probability of discarding a new investment decision from 13% to 17%. Apparently, the effect of aggregate uncertainty on the probability of an investment decision is much stronger than the effect of firm-specific uncertainty. This result suggests that even if firm-specific uncertainty changes, firms might find it difficult to deviate substantially from their investment plans. In sum, our results indicate that stabilizing the economic environment would stimulate investment decisions.

6. Conclusion

This article makes three contributions. First, we form three measures of uncertainty from survey data on firms which is based on the firms' expectation errors. We assume that firms make expectation errors because of uncertainty in the economy. One advantage of our measures is that it is intuitively appealing that expectation errors change with the level of uncertainty. If there were no uncertainty, there would not be any expectation errors. We go further and decompose total uncertainty into two components. We name one of the components idiosyncratic uncertainty and the other aggregate uncertainty. Idiosyncratic uncertainty is the variance in the expectation errors made across firms.

One implication of idiosyncratic uncertainty is that when all the firms make the same expectation error, this implies zero uncertainty. On the other hand, aggregate uncertainty is defined as the square of the average expectation error made across firms. Consequently, the aggregate uncertainty measures higher uncertainty when more firms make similar expectation errors.

Our second contribution is the analysis of the relationship between uncertainty measures that we develop and several measures of economic activity. The cross-correlations show significant negative relations between our uncertainty measures and economic activity. Furthermore, the econometric analysis shows that the quantitative effect of uncertainty on production is large. In particular, we show that a 1 standard deviation increase in aggregate uncertainty is followed by a 0.4% decline in year-on-year change of IPI on impact. The prolonged effect reaches 5.9% in a year. Moreover, an analysis of the downturn in 2008–2009 shows that about 44% of the decline in industrial production can be attributed to the increased uncertainty. We further show that of this 44%, 60% comes from aggregate uncertainty, whilst 40% is from idiosyncratic uncertainty.

Finally, we exploit the panel dimension of our data set to provide evidence on the significant effects of aggregate and idiosyncratic uncertainty on firms' investment decisions. According to our findings, firms adjust their investment plans very little due to changes in firm-specific uncertainty, but plans are revised more as a result of a change in aggregate uncertainty. This result indicates that in firms' investment decisions, uncertainty in the economic environment is more important than firm-specific uncertainties. One major shortcoming of this analysis is that, since we construct our uncertainty measures from firms' production expectations, it is not possible to assess the impact of demand and price uncertainty on the investment decisions. To investigate these effects might be the scope of a further study.

The uncertainty measures proposed in this article may provide useful information for policy makers. In particular, when these measures signal a significant increase in uncertainty, policy makers could investigate managers in the real sector by contacting them directly to learn of possible reasons for increased uncertainty. This new information could help one understand the nature of the shock and facilitate taking the necessary actions. On the other hand, it should be noted that this study takes into account only the manufacturing sector, and this limitation should be considered when applying the policy measures.

Supplementary material

Supplementary material is available online at the OUP website.

Acknowledgements

We thank Erdem Başçı, Lawrence J. Christiano, Alpay Filiztekin, Refet S. Gürkaynak, Fatih Güvenen, Vincenzo Quadrini, Juan F. Rubio-Ramírez, Çağrı Sarıkaya, two anonymous referees and seminar participants at the 2011 Midwest Macroeconomics Meetings, 31st CIRET Conference on Economic Tendency Surveys and Economic Policy, the International Economics Association 16th World Congress, and the 2010 Internal Conference of Research and Monetary Policy Department of the Central Bank of Turkey. All errors are ours. The views expressed in this

article are those of the authors and do not necessarily reflect the official view of the Central Bank of Turkey.

References

Atabek, A., Atuk, O., Coşar, E. E., and Sarıkaya, Ç. (2009) Mevsimsel modellerde çalışma günü değişkeni, *TCMB Ekonomi Notları*, **3**.

Atabek, A., Coşar, E. E., and Şahinöz, S. (2005) A new composite leading indicator for Turkish economic activity, *Emerging Markets Finance and Trade,* **41**, 45–64.

Bachmann, R., and Bayer, C. (2013) Wait-and-see business cycles?, *Journal of Monetary Economics,* **60**, 704–19.

Bachmann, R., Elstner, S., and Sims, E. (2013) Uncertainty and economic activity: evidence from business survey data, *American Economic Journal: Macroeconomics,* **5**, 217–49.

Bachmann, R., and Moscarini, G. (2011) Business cycles and endogenous uncertainty. In *2011 Meeting Papers* (No. 36), Society for Economic Dynamics, St. Louis, MO.

Baker, S. R., Bloom, N., and Davis, S. J. (2013) Measuring economic policy uncertainty, available at http://www.policyuncertainty.com/media/BakerBloomDavis.pdf (accessed 11 November 2014).

Basu, S., and Bundick, B. (2012) Uncertainty shocks in a model of effective demand, NBER Working Paper No. w18420, Cambridge, MA.

Bloom, N. (2009) The impact of uncertainty shocks, *Econometrica,* **77**, 623–85.

Bloom, N., Bond, S., and Van Reenen, J. (2007) Uncertainty and investment dynamics, *Review of Economic Studies,* **74**, 391–415.

Bloom, N., Floetotto, M., Jaimovich, N., Saporta-Eksten, I., and Terry, S. J. (2012) Really uncertain business cycles, NBER Working Paper No. w18245, Cambridge, MA.

Bomberger, W. A. (1996) Disagreement as a measure of uncertainty, *Journal of Money, Credit and Banking,* **28**, 381–92.

Christiano, L., Motto, R., and Rostagno, M. (2013) Risk shocks, NBER Working Paper No. w18682, Cambridge, MA.

Denis, S., and Kannan, P. (2013) The impact of uncertainty shocks on the UK economy, IMF Working Paper No. 13/66, Washington, DC.

Fernández-Villaverde, J., Guerrón-Quintana, P. A., Kuester, K., and Rubio-Ramírez, J. (2011) Fiscal volatility shocks and economic activity, NBER Working Paper No. w17317, Cambridge, MA.

Gilchrist, S., and Zakrajšek, E. (2012) Credit spreads and business cycle fluctuations, *American Economic Review,* **102**, 1692–720.

Guiso, L., and Parigi, G. (1999) Investment and demand uncertainty, *Quarterly Journal of Economics,* **114**, 185–227.

Johannsen, B. K. (2014) When are the effects of fiscal policy uncertainty large? Federal Reserve Board, Finance and Economics Discussion Series 40, Washington, DC.

Jurado, K., Ludvigson, S. C., and Ng, S. (2013) Measuring uncertainty, NBER Working Paper No. w19456, Cambridge, MA.

Leahy, J. V., and Whited, T. M. (1996) The effect of uncertainty on investment: some stylized facts, *Journal of Money, Credit and Banking,* **28**, 64–83.

Leduc, S., and Liu, Z. (2012) Uncertainty shocks are aggregate demand shocks, Federal Reserve Bank of San Francisco Working Paper 10, San Francisco, CA.

Lorenzoni, G. (2009) A theory of demand shocks, *American Economic Review,* **99**, 2050–84.

Lorenzoni, G. (2010) Optimal monetary policy with uncertain fundamentals and dispersed information, *Review of Economic Studies,* **77**, 305–38.

McKay, A., and Reis, R. (2008) The brevity and violence of contractions and expansions, *Journal of Monetary Economics,* **55**, 738–51.

Morris, S., and Shin, H. S. (2002) Social value of public information, *American Economic Review*, **92**, 1521–34.

Mumtaz, H., and Zanetti, F. (2013) The impact of the volatility of monetary policy shocks, *Journal of Money, Credit and Banking*, **45**, 535–58.

Orlik, A., and Veldkamp, L. (2014) Understanding uncertainty shocks and the role of the black swan, NBER Working Paper No. w20445, Cambridge, MA.

Scotti, C. (2013). Surprise and uncertainty indexes: real-time aggregation of real-activity macro surprises, Federal Reserve Board International Finance Discussion Paper No. 1093, Washington, DC.

Shoag, D., and Veuger, S. (2014) Uncertainty and the geography of the great recession, American Enterprise Institute Working Paper No. 38809, Washington, DC.