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Click to Download Data: An Event Study of Internet Access to Economic Statistics*

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Abstract

This study examines the online access statistics of the Central Bank of Turkey's Electronic Data Delivery System within an event study framework. The comparisons of pre-event and post-event statistics suggest that announcements of both the policy interest rates and the consumer price data considerably affect society's data access behavior. The timing and amplitude of these effects are further studied with respect to inflation expectations and surprise content of events; yet no solid pattern was revealed.

JEL Classification: C50, G10 and G14.
Keywords: Data access, Macroeconomic data, Market efficiency, Event study.

* All the views expressed in this paper belong to the authors and do not represent those of the Central Bank of the Republic of Turkey, or its staff.

1. Introduction

In a recent study of ours (Tokel and Yucel, 2009), we examined the access behavior to Central Bank of Turkey's (CBT) data dissemination system (EDDS[1]) and concluded that certain calendar patterns in data access could not be denied. In doing so, we provided the formal hypothesis tests within a Generalized Autoregressive Conditional Heteroskedasticity (GARCH) framework. Admitting the simplicity of analysis in Tokel and Yucel (2009), the paper provided a good insight with regard to the topic at hand.

The motivation in Tokel and Yucel (2009) has originated from the observation that society's tendency to utilize more concrete/solid data increased during the last two decades mainly owing to the technical advances in information technologies. Meanwhile, philosophical advances in understanding the importance of transparency and data dissemination played an important part. Consequently, people demand more data compared to previous years and whenever possible, they perform their own computations by employing raw data. Then, it is not surprising that general economic data gained an enormous pace both in terms of volume and coverage.

Nevertheless, regularities in data access behavior must not only occur in terms of simple calendar effects. Although existence and importance of calendar effects cannot be denied, a deeper understanding requires establishing the connections between data access behavior and well-defined instances and/or economic events. This question, which we have admitted yet not being analyzed in Tokel and Yucel (2009), establishes the starting point of the current study.

In the subsequent sections, we employ an event study framework in analyzing the same data as employed in Tokel and Yucel (2009). Benefits of this approach is believed to be two-fold: First, effects of certain economic events on people's data access behavior can be more accurately extracted by means of an event study; second, each instance of a type of event can be further examined in isolation. More importantly, technical complications of alternative techniques are avoided by employing an event study approach. In this framework, it is hypothesized that the data access figures before and after an economic event differ. The events that we

[1] For more information on EDDS, see http://evds.tcmb.gov.tr/yeni/cbt-uk.html.

consider are (1) CBT's interest rate announcements and (2) TURKSTAT's official announcement of monthly CPI data.

In Section 2, a brief review of the event study methodology is provided. In Section 3, we reiterate the main points about access data for Central Bank of Turkey's Electronic Data Dissemination System. Section 4 is devoted to analytical results and discussion. Section 5 concludes the paper.

2. A. Bird's Eye View of Method

The event study approach has many applications in addition to its more traditional function as a means of measuring the effects of an economic event on the value of firms. Taking rational behavior as given in the marketplace, the effects of an event are expected to reflect instantaneously upon security prices. Some traditional examples of event study applications deal with mergers and acquisitions, earnings announcements, issues of new debt or equity, and announcements of macro- economic variables such as the trade deficit. Applications in other fields, such as law and economics and damage assessments are known as well (Schwert, 1981; Mitchell and Netter, 1994). An extensive survey of the event study literature and methodological details can be found in MacKinlay (1997) from which we borrow a lot in this section.[2]

Following MacKinlay (1997), we can list the stages of an event study. This, of course, does not necessarily mean that there is an all-purpose cookbook (formally an algorithm) fitting all possible cases. The listed stages can rather be seen as general guidelines to establish a sound framework.

2.1. Stages of an Event Study

[1] The initial task is to define the event of interest and the event window. Definition of the event is preferred not to be vague and there should be very little room for discretion and/or dispute regarding its implementation.

[2] Under usual circumstances, identification of an event must be followed by the determination of selection criteria for the inclusion of a given firm in the study.

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[2] For an earlier bundle of event studies, see Dolley (1933), Myers and Bakay (1948), Barker (1956, 1957, 1958), Ashley (1962), Ball and Brown (1968) and Fama et al. (1969). A number of modifications, then, have been developed; see Brown and Warner (1980, 1985), which addresses the practical importance of many of the related complications.

As the event study approach was mainly established as a means to understand abnormal returns, selection of the firms to consider is a critical element of analysis. In our case, on the other hand, this stage drops out since there is a single object of analysis, namely the EDDS data access counts.

[3] A definition of the "normal" behavior is then necessary. This is achieved via a numerical (i.e. formal) model. The normal behavior establishes the baseline needed to make comparisons between pre-event and post-event windows (In order to have a full definition of different kinds of event windows see MacKinlay, 1997). The parameter estimates for the normal behavior (originally normal performance or normal returns), the abnormal behavior (originally abnormal returns) can be calculated.

[4] The final stage is to formally assess the degree of abnormality of returns. This entails a series of formal statistical tests. The testing framework might include several techniques ranging from parametric statistical tests to more flexible nonparametric frameworks.

2.2. Implementation Details: This Paper

Before going into next sections where we describe our data and analytical results, it might be useful to provide more details about our analytical environment. We expect these details to eliminate the readers' discomfort once the partial mismatch between the current implementation and the stages summarized above is realized.

[1] We examine two events. The first is the CBT's announcement of its policy interest rate decisions. The second event is the official dissemination of CPI data by TURKSTAT. As the dates of both kinds of events are known beforehand, there is no surprise element with regard to timing of these events. However, both kinds of events might have some "surprise value" conditional upon their exact contents. For instance, if an interest rate announcement does not match the market expectations (downward or upward), it is interpreted as a surprise. The same is valid for newly disseminated CPI data. Once the announced rate of CPI inflation considerably differs from expected figures, one may mark such happening as a surprise. Prior to analysis, we do not distinguish individual instances of our two events with respect to their surprise content. Impact of surprise content is considered in a later step.

[2] As mentioned above, no selection criteria are needed given that the object of analysis, namely the EDDS data access statistics, is unique.

[3] Pre-event[3] behavior is defined by the average data access from day (-t) to day (-1) for each time interval [-t, 0). For convenience, this entity is named ADA(-t). The event day itself is not included while computing the averages. Use of arithmetic averages corresponds to the "constant mean return model" as summarized in MacKinlay (1997).

[4] Abnormalities of data access counts are then assessed by means of comparisons between ADA(-t) and ADA(t). Needless to mention, ADA(t) is the average data access between post-event day (0) to day (t). As ADA(-t) and ADA(t) are computed for each day in [1,T], where T denotes the maximum window size, we have T separate comparisons of pre-event and post-event statistics.

2.3. Clarifications

Use of comparisons between pre-event and post-event ADA figures might require further clarifications, which are presented below:

[C1] Dates of all events here are known beforehand. Therefore, labeling the pre-event behavior as "normal" generates a bias at the very beginning. Having known the event dates, economic agents' data access behaviors might have already been affected.

[C2] As a remedy, one may consider fitting a general behavior for the full data sample and assessing the distance between the pre-event behavior and this general behavior. For the purposes of this paper, such a practice seems to have no value added since our aim is to more straightforwardly compare the pre-event and post-event.

[C3] Still, the general trend in time series data must not be ignored, at least based on the evidence of strong upward trend in data access counts documented in Tokel and Yucel (2009). We address this issue by using the de-trended data access counts in the upcoming sections of this study. Use of de-trended data partially addresses [C2].

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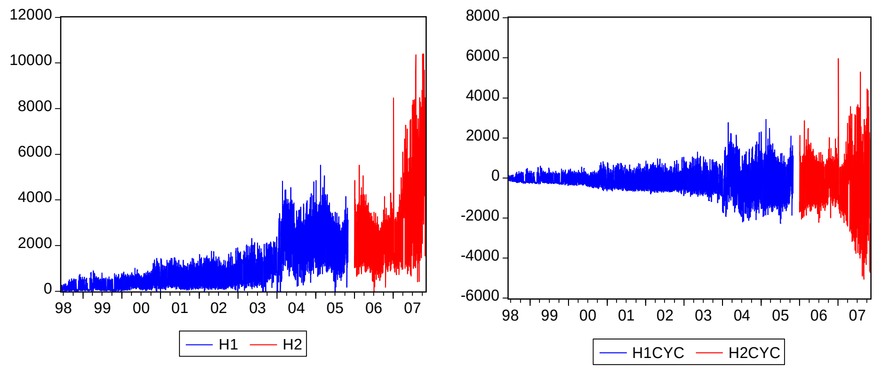
[3] We avoid using the term "normal" on purpose. Please see the subsection entitled "Clarifications".

Figure 1. Number of EDDS Queries (daily)

Original Data **Deviations from Hodrick-Prescott (HP)Trend**



Left – Blue segment (H1): June 12th 1998 - November 1st 2005, Red segment (H2): January 1st 2005 – October 31st 2007. Right – Same periods, deviations from HP trend. Source: Tokel and Yucel (2009).

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Table 1
Descriptive Statistics of EDDS Access Data (daily)

	H	H1	H2
Mean	1489.69	1061.28	3218.05
Median	979.00	766.00	2863.00
Max / Min	10402.00 / 0.00	5523.00 / 0.00	10402.00 / 0.00
Std. Dev.	1539.29	1012.16	2017.88
Sample Size	3368	2699	669

Source: Tokel and Yucel (2009).

Box 1. Computations and Visuals Guide

Boxes normally belong to official reports rather than academic papers. This time, as an attempt to clarify the material presented in this paper, we have thought it might be innovative to use a box. Honestly speaking, this eliminated some efforts needed to clarify the text itself.

Below provided is a map of the computational and visual ingredients of the paper.

[:] Analysis begins with defining the events and selecting the instances. The events are (1) CBT's interest rate announcements and (2) TURKSTAT's CPI data announcements. Each individual realization of a selected event is an instance of that event (Section 2.2, 3.2).

[:] Pre-event and post-event windows are the periods over which we define normal behavior and "affected behavior", respectively (Section 2.2 and 4.2).

[:] The raw data are the daily EDDS data access counts with weekends eliminated (Section 3.1, Figure 1, Table 1). So data access counts are used in two forms: Original and de-trended.

[:] ADA(-t) is an average of data access counts from day (-t) to (-1). Similarly ADA(t) is an average of data access counts from day (1) to (t). Notice the dynamic nature of this definition (Section 4.2).

[:] Elimination of HP trend and averaging are the only transformations applied to data set (Section 3.1).

[:] Appendix provides a full-length documentation of the original data, its ADA version as well as the de-trended data and its ADA version.

[:] Each ADA(t) is compared to respective ADA(-t). D(t) is defined as the difference between ADA(t) and ADA(-t) (Section 4.2).

[:] Accumulation of D(t) over day 1 to day 5 gives us DI(5). Choice of 5 days is to avoid the interference of our events (Section 4.2, 4.3).

[:] Figures 2 to 5 summarize the measure D(t) for all cases in summary form as heat maps.

[:] An instance of an event is considered to have a considerable impact on data access behavior if DI(5) for that instance is at least 3 (Section 4.2).

[:] Table 2 and Table 3 provide the reader with impact summaries for each event and classify the instances with respect to their degree of impact values.

3. Data

3.1. EDDS Usage Data

The EDDS usage data were obtained from the EDDS itself. Usage data on EDDS have been available for the period from June 12th, 1998 to October 31st, 2007; with no documented reason with regard to the suspension of dissemination.[4] Furthermore, usage data are discontinuous from November 1st 2005 to December 31st 2005. This blackout period imposes some limitations on empirical analysis. While analyzing the calendar effects embedded in data access figures, this blackout period imposed some analytical limitations. Due to the two-month gap in data series, use of sub-samples was almost unavoidable. In the present case, however, missing data do not cause a similar problem. The reader will reveal that at most three instances (events) are sacrificed.

Figure 1 displays the evolution of EDDS data access counts against time. As one may realize the original series, named h, is highly volatile (descriptive statistics of the overall data set are given in Table 1). Indeed, this was the fundamental reason for setting the modeling strategy as GARCH, after appropriate preliminary testing, in Tokel and Yucel (2009). High volatility, however, does not constitute a severe problem for our analysis.

We use two versions of daily data access counts: (1) Original series (h), (2) Deviation of original series from its long-term trend (hcyc) estimated via Hodrick-Prescott (HP) filter. While obtaining the HP trend, all available observations of h were used and the above-mentioned blackout was addressed by implementing the filter separately on each subsample (see Tokel and Yucel 2009). Detrending is seen here as a critical element of data transformation. The presence of trend might shadow the comparisons of h before and after the point of event.

A final point regarding the data and transformation issues is the presence of the day of the week effects in EDDS access counts as documented in Tokel and Yucel (2009). Having observed that low data access counts concentrated especially on weekends, we omitted the weekend data from our sample throughout the

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[4] The EDDS usage data does not give any clues on whether the access counter keeps records of multiple accesses from the same client IP within a short period. In addition, access statistics for individual data items is not provided. If such data were at hand, it would be more meaningful to conduct such an analysis, yet what is at hand may suffice.

consequent event study. Note that, no further transformation is implemented after omission of weekends so as not to distort the information content of h and hcyc.

3.2. Event Data

The dates of CBT's interest rate decisions are taken from the official web site of the CBT[5] by scanning a number of announcements and press releases. Since the overnight interest rate was designated as the monetary policy instrument after February 2001, the number of interest rate decisions is not ample. There are 55 interest rate decision announcements between February 2001 and October 2007, the earliest (latest) of which is 16 July 2001 (16 October 2007). Realize that the suspension of EDDS data after November 2007 limits the number of cases that we investigate.

Dissemination of CPI data by TURKSTAT, on the other hand, occurs on the 3rd of each month. Before 2006, this date was shifted to the first subsequent workday in the case that 3rd of the month coincides with weekend. After 2006, coincidence with weekends has been remedied by shifting the dissemination day to the nearest workday. There are 82 CPI announcements between January 2001 and October 2007, the date of the earliest (latest) being 3 January 2001 (3 October 2007).

Note that three instances have to be skipped due to the blackout of EDDS access data during November-December 2005. This leaves us with 52 announcements of interest rates and 79 announcements of CPI data, a full list of which can be seen in the Appendix.

4. Analysis

In the previous sections we explained our variables of concern. Here it might be useful to reiterate the definitions of our variables along with some intuition:

[•] Based on the evidence documented in Tokel and Yucel (2009), the weekends are removed from the daily EDDS access data.

[•] Both the pre-event and post-event windows have a length of 15 workdays. However, the two types of events, in a large portion of our sample, may have effects that are not disjoint (interference of events). This introduces some

[5] http://www.tcmb.gov.tr

complication while interpreting the results. We address this issue in the subsequent parts of the text, when necessary.

[•] The EDDS data access counts constitute the original series.

[•] Averages of the EDDS access counts are also computed from each date T (inclusive) to the event day (exclusive). This further smoothes up the series and facilitates better comparisons.

[•] Deviations of EDDS data counts from their respective Hodrick-Prescott filter trend are used to remove the bulk impact of the inherent trend process.

[•] Averages of the deviations are the last alternative definition of data employed in our analysis.

4.1. Heat Map Presentation of Results

Using these ingredients, we first perform a visual inspection of the patterns embedded in the data. The statistics of interest within a ±15 day symmetric set of windows surrounding the event day are presented in the Appendix. At an initial stage, this so long sequence of graphs is summarized in Figures 2 through 5. These figures display the post-event – pre-event differences in a manner similar to that of heat maps.[6] A hotter (colder) color on a certain day of a selected instance indicates a higher (lower) post-event – pre-event difference. On average, in Figures 2 to 5, yellow-to-dark red regions are concentrated around (1) the first couple of days after the event day and (2) the more recent dated instances. This might be indicative of the increased data access after the event day in recent past as compared to more distant instances. Nevertheless, this evidence is not strong enough to make a general and solid conclusion.

4.2. How About the Individual Instances?

The next stage is the one-by-one analysis of our instances (52 for interest rate announcements and 79 for CPI data releases). While doing so, we first examine each instance in isolation and present similar instances together. The results of this

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[6] As a matter of fact, the presented heat maps can be seen as a stacked presentation of the bar charts introduces in the Appendix. The major difference is that the pre-event bars are subtracted from post-event bars prior to mapping. In addition, while generating the heat maps, we use an interpolated color scheme so that a continuous transition between subsequent colors is ensured.

exercise are consolidated in Table 2 (for interest rate announcements) and in Table 3 (for CPI data announcements).

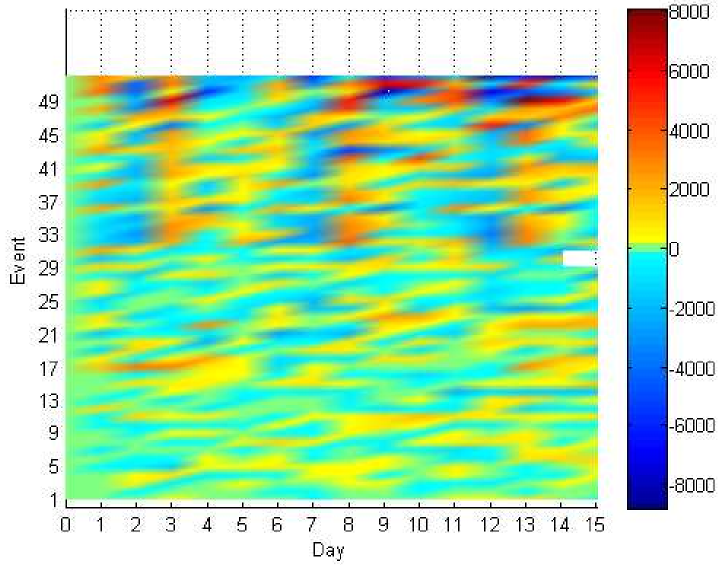
The impatient reader may view a discussion of the interference of events and role of surprises in the following subsections.

Figure 2. Post-event – Pre-event Differences

CBT's Interest Rate Announcements – Original EDDS Access Counts

Upper: Difference between Pre-event – Post-event Levels

Lower: Difference between Pre-event – Post-event Averages



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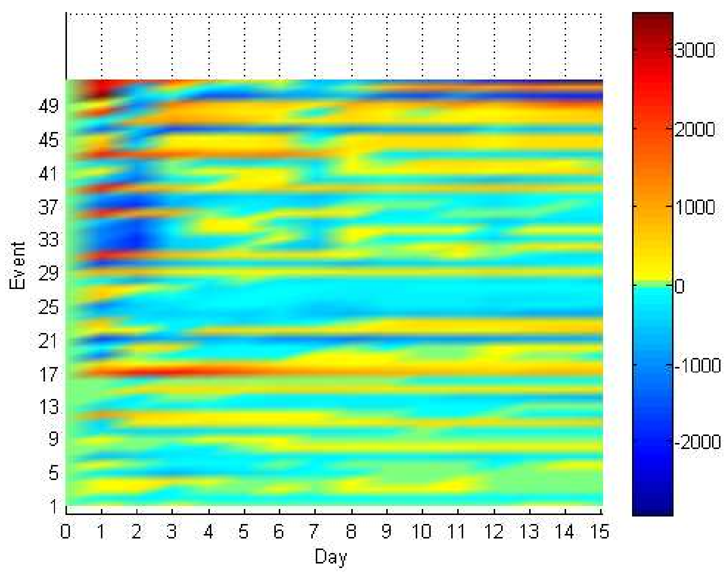


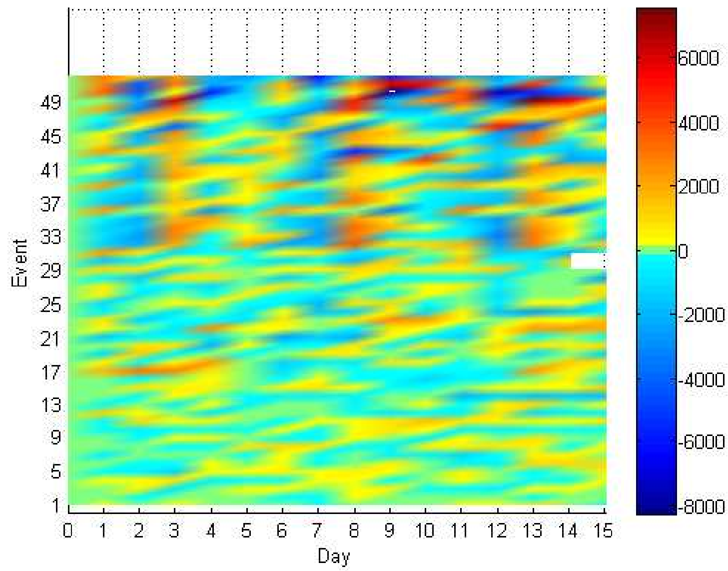
See Appendix to match event numbers with event dates. The value on date (t) corresponds to the difference of considered statistic between date (t) and date (-t).

Figure 3. Post-event – Pre-event Differences

CBT's Interest Rate Announcements – Deviations of EDDS Access Counts from HP Trend

Upper: Difference between Pre-event – Post-event Levels

Lower: Difference between Pre-event – Post-event Averages



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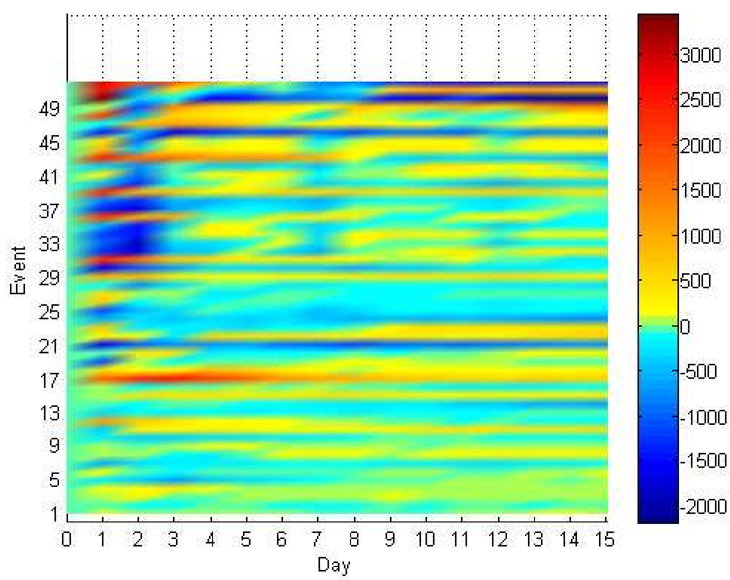
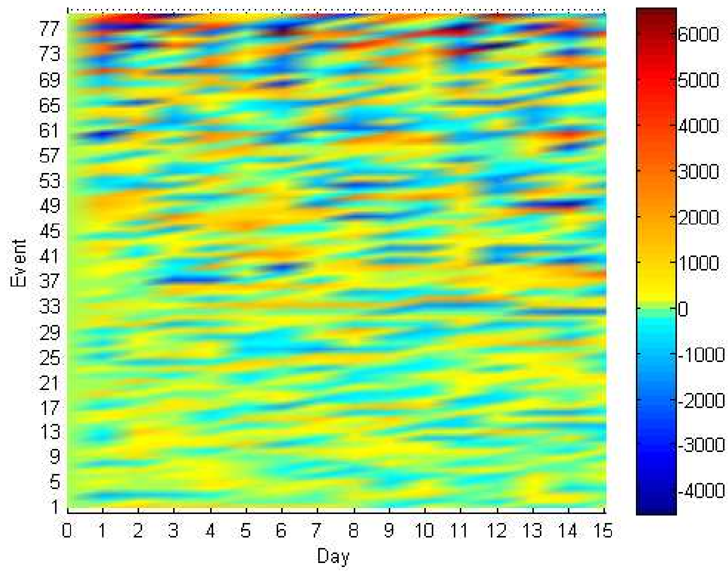


See Appendix to match event numbers with event dates. The value on date (t) corresponds to the difference of considered statistic between date (t) and date (-t).

Figure 4. Post-event – Pre-event Differences
TURKSTAT's CPI Announcements – Original EDDS Access Counts
Upper: Difference between Pre-event – Post-event Levels
Lower: Difference between Pre-event – Post-event Averages



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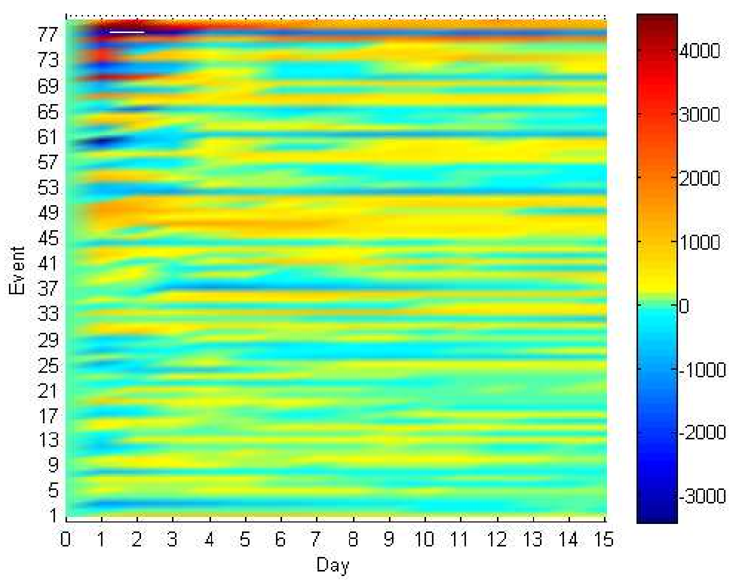
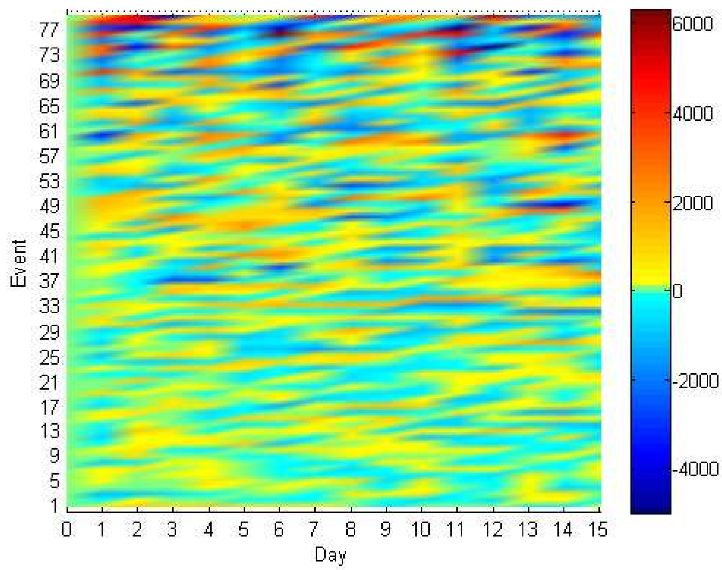


See Appendix to match event numbers with event dates. The value on date (t) corresponds to the difference of considered statistic between date (t) and date (-t).

Figure 5. Post-event – Pre-event Differences
TURKSTAT's CPI Announcements – Deviations of EDDS Access Counts from HP Trend
Upper: Difference between Pre-event – Post-event Levels
Lower: Difference between Pre-event – Post-event Averages



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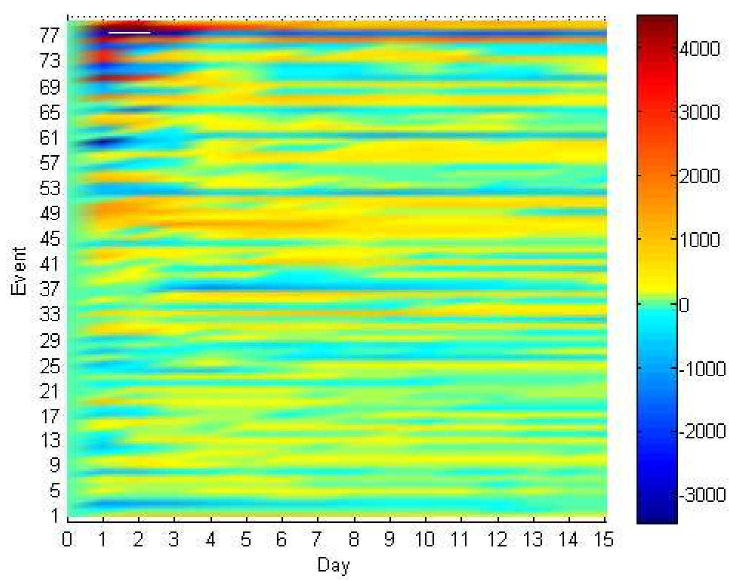

See Appendix to match event numbers with event dates. The value on date (t) corresponds to the difference of considered statistic between date (t) and date (-t).

Construction of Table 2 and Table 3 is not complicated. Indeed, it is not more than a rigorous counting exercise: Remember that we hypothesize an increase in the data access behavior. In order to assess the effects of our events, we employ the averages of the cyclical component of EDDS data access figures. This variable has previously been defined as ADA(-t) for each pre-event day (-t), and ADA(t) for each post-event day (t). The difference ADA(t)-ADA(-t), call this DIF(t) provide us with the necessary information about the effects of event instances. We compute D(t) from t=1 to t=15. In this way, we obtain a rich set of statistics.

Table 2
Impact Summary (Interest Rate Announcements)

Degree of Impact	List of Instances	Count [Percentage]
5	(A1, 16-Jul-01), (A4, 04-Sep-01), (A12, 04-Jun-03), (. 15, 18-Sep-03), (A17, 05-Feb-04), (A18, 17-Mar-04), (A29, 09-Sep-0 (A31, 23-Jan-06), (A39, 26-Sep-06), (A43, 16-Jan-07), (A52, 16-Oct-07	**11 [21%]**
4	(A9, 05-Aug-02), (A11, 25-Apr-03), (A22, 09-Feb-05), (A44, 15-Feb-07), (A45, 15-Mar-07), (A47, 14-May-07), (A48, 14-Jun-07), (A49, 12-Jul-07)	**8 [15%]**
3	(A3, 27-Aug-01), (A27, 11-Jul-05), (A36, 20-Jun-06), A41, 23-Nov-06)	**4 [8%]**
2	(A8, 30-Apr-02), (A16, 15-Oct-03), (A20, 20-Dec-04), (A34, 27-Apr-06), (A35, 25-May-06), (A51, 13-Sep-07)	**6 [12%]**
1	(A6, 14-Mar-02), (A19, 08-Sep-04), (A23, 09-Mar-05 (A26, 09-Jun-05), (A32, 23-Feb-06), (A40, 19-Oct-06), (A50, 14-Aug-0	**7 [13%]**
0	(A2, 06-Aug-01), (A5, 20-Feb-02), (A7, 08-Apr-02), (A10, 11-Nov-02), (A13, 16-Jul-03), (A14, 06-Aug-03), (A21, 11-Jan-05), (A24, 11-Apr-05), (A25, 10-May-05), (A28, 09-Aug-05), (A30, 11-Oct-05), (A33, 23-Mar-06), (A37, 20-Jul-06), (A38, 24-Aug-06), (A42, 21-Dec-06), (A46, 18-Apr-07)	**16 [31%]**

Nevertheless, an array of D(t), t=1,..,15, can be messy and needs more elaboration. As a final step, we count the number of days within a five-day window where D(t) is positive, call this DI(5)[7]. By definition DI(5) can take values between zero and five. The case that DI(5) represents the case where a selected instance has impacted the EDDS data counts upward in each of the five days after the event as compared to equidistant days before the event. In our consequent assessments, we consider values of DI(5) greater than two as solid visual evidence.[8] Notice that

[7] Since we use a five-day window, the impact measure is called DI(5). If one uses a different window width, like 8, the measure will then be named DI(8) and it will count the number of days within an eight-day window where D(t) is positive.
[8] Realize that the computation of D(t) and DI(5) only facilitates a visual assessment of results. At this stage we still have not considered any formal testing.

when DI(5) equals 2, pre-event ADA(-t) figure is larger than or equal to the post-event ADA(t) for three days within a five-day window.

DI(5) values are shown in the first columns of Table 2 and Table 3. List of instances with a certain DI(5) value accompanied with their counts (and percentages) are provided in the second and third columns, respectively.

Table 2 presents the impact summary of interest rate announcements in line with the above descriptions. It suggests that in 23 out of 52 cases (44%) the EDDS data access has been higher in the post-event compared to the pre-event period, using the criterion that DI(5)>2. More interestingly, among these 23 cases, there are three months from each of the 2001, 2003 and 2005, two months of 2004, one month of 2002 and four months of 2006. The year 2007, on the other hand, appears 7 times in the first three rows of Table 2.

Table 3
Impact Summary (CPI Data Announcements)

Degree of Impact	List of Instances	Count [Percentage]
5	(A1, 03-Jan-01), (A5, 03-May-01), (A6, 04-Jun-01), [illegible]7, 03-Jul-01), (A9, 03-Sep-01), (A10, 03-Oct-01), (A16, 03-Apr-02 [illegible] (A19, 03-Jul-02), (A23, 04-Nov-02), (A30, 03-Jun-03), (A31, 03-Jul-0[illegible] (A33, 03-Sep-03), (A35, 03-Nov-03), (A39, 03-Mar-04), (A42, 03-Jun-[illegible]), (A43, 05-Jul-04), (A47, 03 Nov-04), (A48, 03-Dec-04), (A49, 03-Jan-[illegible]), (A50, 03-Feb-05), (A54, 03-Jun-05), (A58, 03-Oct-05), (A63, 05-Jun-0[illegible] (A64, 03-Jul-06), (A67, 03-Oct-06), (A70, 03-Jan-07), (A73, 03-Apr-0[illegible], (A76, 03-Jul-07), (A78, 03-Sep-07), (A79, 03-Oct-07)	**30 [38%]**
4	(A4, 03-Apr-01), (A13, 03-Jan-02), (A15, 04-Mar-02), (A20, 05-Aug-02), (A21, 03-Sep-02), (A26, 03-Feb-03), (A41, 03-May-04), (A45, 03-Sep-04), (A46, 04-Oct-04), (A51, 03-Mar-05), (A55, 04-Jul-05), (A66, 04-Sep-06), (A69, 04-Dec-06), (A74, 03-May-07)	**14 [18%]**
3	(A11, 05-Nov-01), (A14, 04-Feb-02), (A18, 03-Jun-[illegible]), (A25, 03-Jan-03), (A36, 03-Dec-03), (A57, 05-Sep-05), (A62, 03-May-[illegible])	**7 [9%]**
2	(A12, 03-Dec-01), (A17, 03-May-02), (A29, 05-May-03), (A38, 03-Feb-04), (A40, 05-Apr-04), (A53, 03-May-05), (A56, 03-Aug-05), (A59, 03-Feb-06), (A60, 03-Mar-06), (A68, 03-Nov-06), (A71, 02-Feb-07)	**11 [14%]**
1	(A2, 05-Feb-01), (A27, 03-Mar-03), (A28, 03-Apr-0[illegible] (A32, 04-Aug-03)	**4 [5%]**
0	(A3, 05-Mar-01), (A8, 03-Aug-01), (A22, 03-Oct-02), (A24, 03-Dec-02), (A34, 03-Oct-03), (A37, 05-Jan-04), (A44, 03-Aug-04), (A52, 04-Apr-05), (A61, 03-Apr-06), (A65, 03-Aug-06), (A72, 02-Mar-07), (A75, 04-Jun-07), (A77, 03-Aug-07)	**13 [16%]**

Overall, with regard to the interest rate announcements, it is hard to say that they induce a clear-cut increase in EDDS data access. Still, the dominance of 2007 within the cases where DI(5)>2 might deserve further consideration.

Table 3 does the same for CPI data announcements. In that, in 51 out of 79 cases DI(5) is greater than 2. This roughly corresponds to 65% of all CPI announcement instances of our data span and a good sign of people's elevated interest in data once new inflation figures are officially disseminated. Simultaneously, this finding is not indicative of any innovation: people do download data when available. As opposed to the case of interest rate announcements, there is not much differentiation of years in terms of their impacts.

At the end, there is some tangible evidence for the increase of data access figures in the post-event window compared to the pre-event window. Yet, this evidence seems partial in the absence of formal statistical tests.

4.3. Interference of Events

As we mentioned earlier in the text, and as he careful reader have already identified, the two types of events that we consider do not have mutually exclusive time domains. That is, in practically all of the cases, new CPI data announcements are in vicinity of CBT's interest rate announcements. In such a case, the counting exercise of the previous subsection could have been jeopardized.

We have avoided this risk by computing the degree of impact (DI) of the previous subsection for a narrow window of five days.[9] Hence the interference of the two types of events is not explicitly addressed by other means.

4.4. Do Surprises Have a Role?

A natural question in the current context is whether surprises have any effect on the people's data access demands. Does data downloads increase when actual inflation exceeds the expected inflation? Is this relationship (if any) linear or is there some kind of threshold effects? These questions and the like are potentially there waiting for their answers. In this section we try to find an answer.

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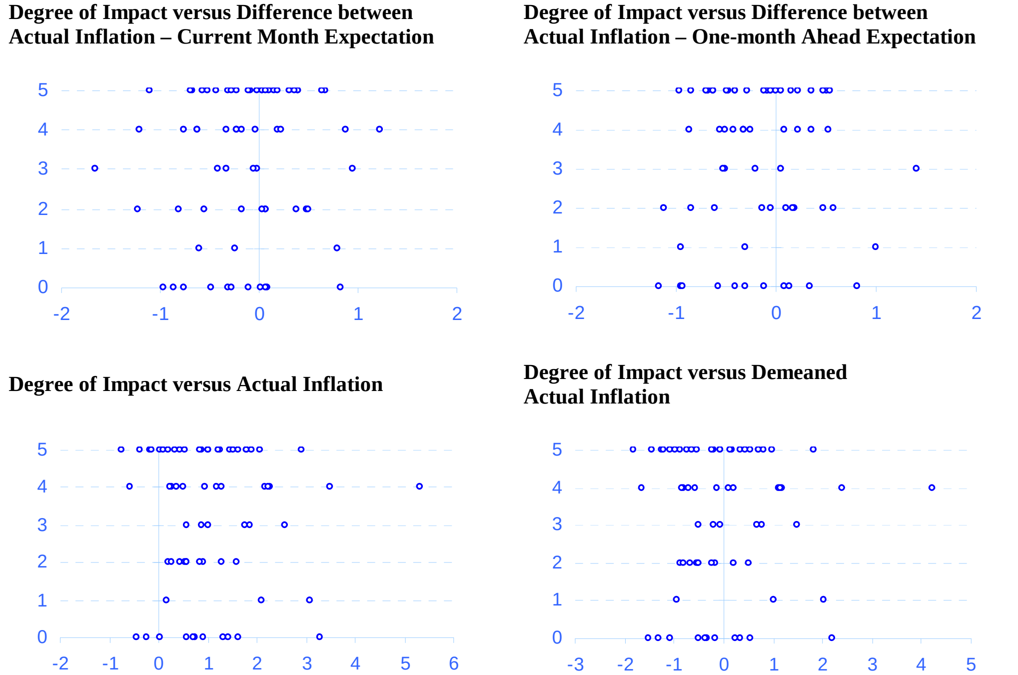
[9] Remembering that the weekends have been omitted beforehand, this still remains a non-negligibly long time period.

Figure 6. Surprises and Data Access



The vertical axes show the degree of impact (DI(5)) values. The horizontal axes display the hypothesized independent variables of interest.

In Figure 6, we plot the degree of impact values used above against different variables. Here, we study only the DI(5) values for the analysis of CPI announcement instances.

In the upper-left panel, DI(5) is scattered against the difference between actual inflation and current month's CPI inflation expectations.[10] The difference is supposed to measure the surprise in inflation. The upper-right panel does the same for the difference between actual inflation and one-month ahead CPI inflation expectations. The lower panels, on the other hand, plot the degree of impact against the actual CPI inflation (demeaned in the lower-right panel).

What Figure 6 suggests is not that informative: It is hard to state a clear-cut relationship between the degrees of impact and the surprise content of CPI inflation. For convenience we provide yet another counting exercise in Table 4. There we

[10] All expectation series used in this section are taken from the CNBC-e Survey of Expectations. We thank Hande Sevgi for her assistance with data compilation.

reveal that the likelihood of a DI value to be associated with a negative inflation surprise rather than a positive one practically does not depend on the magnitude of DI. One may verify this by comparing the ratios 13/11 (14/10) and 26/17 (25/15) in Table 4.

Table 4
Further Counting Figure 6

	Figure 6 Upper-left Panel		Figure 6 Upper-right Panel	
	LOW DI (DI<3)	HIGH DI (DI>2)	LOW DI (DI<3)	HIGH DI (DI>2)
Negative Inflation Surprise	13	26	14	25
Positive Inflation Surprise	11	17	10	15

5. Concluding Remarks

In this paper, we examined the online access statistics of the Central Bank of Turkey's Electronic Data Delivery System within an event study framework. In a way, the analysis completes the treatment of Tokel and Yucel (2009) where we investigated the calendar effects within a GARCH framework.

In our assessments, we defined and considered two types of events: (1) CBT's interest rate announcements and (2) TURKSTAT's official announcement of monthly CPI data. Both of these deserve attention as they gained an ever-increasing importance in the post-2001-crisis episode of the Turkish economy. We performed our analysis using a slightly modified version of the scheme of event studies described in MacKinlay (1997).

The comparisons of pre-event and post-event statistics suggest that announcements of both the policy interest rates and the consumer price data considerably affect society's data access behavior. The timing and amplitude of these effects are further studied with respect to inflation expectations and surprise content of events; yet no solid pattern was revealed.

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Appendix

The graphs of data access figures and related statistics are provided in full-length in the working paper version at http:// mpra.ub.uni-muenchen.de/ 16833/ 1/ MPRA_paper_16833.pdf

In Appendix A of the working paper, we provide the graphs for the instances of Central Bank's policy interest rate announcements. Instances of TURKSTAT's CPI data announcements are given in Appendix B. In Appendix A and B, a standard graphical outline is employed.

[+] On top of each graph, the alphanumerical code of the instance is provided. A1 (B1) simply denotes the first instance of Appendix A (B).

[+] On top of each graph, date of the event day (day zero) is also given.

[+] Each graph consists of four panels

[+] Upper-left panel: Original series (EDDS data counts)

[+] Upper-right panel: Averages over (0,T] of original series (refer to the definition of ADA in the main text)

[+] Lower-left panel: Deviations of original series values from HP trend

[+] Lower-right panel: Averages over (0,T] of de-trended series

[+] In each panel, the days before the event day are marked with their "time-to-event" values. For example, the value of (-5) corresponds to the fifth day before the event, zero is the event day and 5 is the fifth day after the event. For convenience, different colors are used for before event, event and after event series. Numerical scale of the vertical axis may vary between graphs so as to ensure best visualization.

The readers may contact the authors for sample pages of the spreadsheet that was used to generate the graphs.