CFDS Discussion Paper Series

Forecast Performance in Times of Terrorism

Jonathan Benchimol, Makram El-Shagi

Discussion Paper 2017/1

AUTHORS

Jonathan Benchimol
Bank of Israel, Jerusalem
E-mail: jonathan.benchimol@boi.org.il
Tel: + 972 -2-6552641

Makram El-Shagi (Corresponding Author)
HenU Center for Financial Development and Stability
Henan University
E-mail: makram.elshagi@gmail.com
Tel: +86 155 6511 5281

IMPRESSUM

HenU Center for Financial Development and Stability
Dongliuzhai Building, 85 Minglun Street
Henan University, Minglun Campus
Shunhe, Kaifeng, Henan, China
Tel. +86 (30) 897 89-0
http://cfds.henuecon.education

Papers can be downloaded free of charge from the CFDS website:
http://cfds.henuecon.education/index.php/research

Forecast performance in times of terrorism*

Jonathan Benchimol[†] and Makram El-Shagi[‡]

Abstract

Governments, central banks, and private companies make extensive use of expert and market-based forecasts in their decision-making processes. These forecasts can be affected by terrorism, which should be considered by decision makers. We focus on terrorism, as a mostly endogenously driven form of political uncertainty, and use new econometric tests to assess the forecasting performance of market and professional inflation and exchange-rate forecasts in Israel. We show that expert forecasts are better than market-based forecasts, particularly during periods of terrorism. However, forecasting performance and abilities of both market-based and expert forecasts are significantly reduced during such periods. Thus, policymakers should be particularly attentive to terrorism when considering inflation and exchange-rate forecasts.

Keywords: inflation, exchange rate, forecast performance, terrorism, market forecast, expert forecast.

JEL Classification: C53, E37, F37, F51.

*This paper does not necessarily reflect the views of the Bank of Israel. We thank Itamar Caspi, Ariel Mansura, Yehuda Porath, Benzion Schreiber, Harald Uhlig, Noam Zussman, and participants at the 49th Money, Macro and Finance Research Group annual conference, Romanian Academy and Bank of Israel's research seminar for their useful comments.

[†]Bank of Israel, Jerusalem, Israel. Email: jonathan.benchimol@boi.org.il

[‡]Center for Financial Development and Stability at Henan University (Kaifeng, China) and Halle Institute for Economic Research (IWH). Corresponding author. Email: makram.el-shagi@cfds.henuecon.education

1 Introduction

In recent years, a rising number of researchers have shown interest in the economic consequences of terrorism, fuelled by the increase in terrorist attacks in highly developed countries that have traditionally been considered as safe. See, for example, Blomberg et al. (2004), Crain and Crain (2006), Dorsett (2013), Gerlach and Yook (2016), and Ruiz Estrada and Koutronas (2016) to name just a few.

Although there has been higher understanding of the real economic impact of terrorism, there is little evidence on the impact of terrorism on expectations. Given that the very definition of terrorism comes down to the aim to "intimidate or create panic,"[1] omission of the more direct psychological impact that can be seen in the expectations seems problematic. Expectations play a pivotal role in the mechanism of state-of-the-art workhorse models of modern macroeconomics. Central banks, other policy makers, and other public and private institutions rely heavily on professional forecasts and market-implied expectations in their decision making.[2] Understanding how a climate of fear generated by terrorism affects those expectations and forecasts is essential for proper policy making.

Thus, in this study, we aim to fill this gap by using data on Israel, the developed country that has been plagued by far the most by terrorist activity.

There seems to be consensus in the literature that rare and infrequent terrorist attacks[3] have a limited direct and immediate economic impact on developed economies (Abadie and Gardeazabal, 2003).

However, persistent terrorism, as observed in Israel, might have a different effect.[4] Eckstein and Tsiddon (2004) show that in the absence of (regular)

[1] According to Webster's New World Law Dictionary, the legal definition of terrorism is "the threat or actual use of violence in order to intimidate or create panic, especially when utilized as a means of attempting to influence political conduct."

[2] See, for example, El-Shagi (2011) and El-Shagi et al. (2016) for a discussion on expectations and forecasts, respectively.

[3] It is important to distinguish different types of terrorism: frequent at low intensity (Israel during the last decade), frequent at high intensity (Iraq and Syria), rare at low intensity (the United States during the last decade), and rare at high intensity (the United States on 9/11, the United Kingdom at London, and France at Paris and Nice).

[4] Although our paper focuses on Israel, there are some general implications. It has been argued that there are differences between the impact of terrorism on the Western countries and Israel because of the profound difference between the terrorism that occurs in these countries. As terrorism is very frequent in Israel, one can foresee, anticipate, and model it, while terrorist attacks remain profoundly unpredictable (black swan) in the Western countries. However, in recent years this is no longer true, as the indexes of France, the United States, and the United Kingdom (Global Terrorism Index, Institute for Economics and Peace) have become very close to that of Israel. Moreover, fatalities caused by a

terrorist attacks, such as the Second Intifada, Israel's per capita GDP would be higher than its actual GDP. For example, currently, house prices in Israel are considerably lower, especially in endangered regions (Elster et al., 2017). Fielding (2003a) demonstrates that the First Intifada—which he interprets as a measure of political uncertainty—has contributed substantially to the low investment rate of Israel, and Fielding (2003b) shows a decline in the amount of investment.

Contrary to the previously mentioned contributions, our paper focuses on the impact of terrorism on expectations and forecasts. To this end, we assess expert forecasts on inflation as well as the exchange rate and market expectations (implied by the price of inflation-indexed bonds and forward exchange rate) in Israel. Before conducting a causal analysis, we will lay the foundation by performing a dynamic analysis of forecast rationality and (relative) forecast performance. Our assessment relies on the tests for (relative) forecast performance and forecast rationality proposed by Giacomini and Rossi (2010) and Rossi and Sekhposyan (2016), respectively, for unstable environments. Based on preliminary evidence gathered by the results of these tests and Giacomini and White (2006), we conduct an explicit analysis of the causes of forecast performance.

Finally, we control for a range of other aspects of uncertainty and instability to ensure our results are not driven by an omitted variable bias. Specifically, we control for financial instability, commodity prices (particularly oil and gas), exchange rate fluctuations, and an econometric forecast of inflation (exchange rate) uncertainty. Because the conditional relative performance test by Giacomini and White (2006) does not allow for control variables, we propose a slight modification, turning the original correlation-based Wald test into a regression-based Wald test.

To our knowledge, our study is the first to conduct a broad analysis of how terrorism affects forecast performance and, particularly, the first to compare several types of forecasts through different terrorism measures. We find that terrorism affects market participants much more than professional forecasters. At least in the case of Israel, the average low performance of market participants seems to be driven mostly by terrorism. In addition, we find that terrorist attacks affect not only the inflation risk premium, but they also matter when inflation forecasts adjusted for risks are considered.

single terrorist attack have been higher in European countries compared with Israel over the last decade. Therefore, we explicitly distinguish between the frequency and magnitude of terrorist attacks. Other differences do, of course, remain. Most importantly, Israel is much smaller than the aforementioned countries, so per capita terrorism is still unusually high for a developed country. Insofar, although the nature of terrorism in the West has changed, application of our results to other countries should be taken with a grain of salt.

Although our key research question is regarding the impact of terrorism on expectations, we also contribute to the growing literature comparing market-implied forecasts and professional forecasts in general (Adeney et al., 2017). Contrary to majority of the literature, we do so fully while accounting for the dynamics of forecast performance, which are commonly ignored.

The remainder of the paper is organized as follows. Section 2 describes the stylized facts and related economic forecasts that are analyzed. Section 3 develops our methodology and econometric techniques used to quantitatively assess the impact of terrorist attacks on economic forecasts. The results are presented in Section 4 and interpreted in Section 5. In Section 6, we outline some policy implications of our findings. Section 7 concludes.

2 Background

Although there is reason to believe that terrorism might affect expectations and thus forecasts, it seems that institutions making regular use of forecasts (such as central banks) ignore this channel.

While many previous studies analyze the impact of terrorism on current economic activity, few, if any, analyze the impact of terrorism on these essential economic forecasts. Unfortunately, Israel is an excellent laboratory in which to study this impact. Section 2.1 presents some stylized facts about terrorism, Section 2.2 describes the market-based and expert forecasts used in this study, and Section 2.3 details further control variables used for the analysis.

2.1 Terrorism and uncertainty

It is well known that *major* terrorist attacks (Keefer and Loayza, 2008; Roberts, 2009), or continuous *small and medium-sized* terrorist attacks (Sandler and Enders, 2008; Benchimol, 2016), affect the economy. The negative impact of terrorism on short-term activities mainly results from the reallocation of internal demand for public consumption (such as insurance, security forces, and investments) to the detriment of more productive investments, causing growth to decrease (Blomberg et al., 2004). Our purpose is to assess how these violent events affect the bias and predictive abilities of experts as well as market-based forecasts.[5]

[5] We conducted different event studies without robust results. Daily variation in market-based and expert forecasts cannot be explained using terrorism. The effect of terrorism or financial uncertainty on expectations does not seem to be immediate but takes time to come about.

In the aftermath of 9/11 and with the rise of terror attacks in the European Union, there has been increasing interest in the economic consequences of terrorism (Crain and Crain, 2006; Dorsett, 2013; Gerlach and Yook, 2016; Ruiz Estrada and Koutronas, 2016) and the reasons behind it (Dreher and Gassebner, 2008; Dreher and Fischer, 2010). In addition, linkages between terrorism and economic policy have been extensively analyzed (Dreher et al., 2010; Dreher and Fuchs, 2011).

In 2001, when terrorists attacked the United States, the US economy was already in recession, but it reached positive growth only two months later. This led to the conclusion that even a major terrorist attack, such as the destruction of the World Trade Center, would have fairly limited economic consequences. Similarly, after the terrorist attacks in Madrid (2004) and London (2005), GDP growth trends of Spain and the United Kingdom were not affected. Even the attacks in Paris (2015) did not show a measurable impact on French consumption. However, in almost all such cases, although the country is geographically or demographically large compared with the consequences of terrorism, expectations—including forecasts—were strongly affected.

The emergence of a small, developed market economy in parallel with a terrorist conflict provides an interesting economic example (Eldor and Melnick, 2004; Caruso and Klor, 2012). Therefore, Israel is an excellent case study of a (small) developed country facing terrorism and war at different levels and frequencies (Eckstein and Tsiddon, 2004; Larocque et al., 2010).

In the past two decades, five episodes of intense violence have occurred in Israel: the Second Intifada (September 2000 to February 2005), the Second Lebanon War (July to August 2006), Operation Cast Lead (December 2008 to January 2009), Operation Pillar of Defense (November 2012), and Operation Protective Edge (July to August 2014).

Unlike most terrorist attacks occurring in Europe or the United States, terrorist attacks in Israel (Fig. 1) have not involved substantial property or infrastructure destruction, except during the First and Second Intifada, but they have sometimes led to substantial casualties (Fig. 2).

Nevertheless, terrorist attacks affect consumers and investors' behavior and, in turn, stock market prices (Shoham et al., 2011). When terrorists strike at almost regular intervals and fear and insecurity win minds and begin to change agents' economic behavior, the quality of economic (expert and market-based) forecasts would be affected by these transitory events.[6]

[6] Indeed, forecasters expect the cost of security policies to increase, thus increasing the expected cost of economic activities and transactions, while large companies are expected to cancel or delay investments.

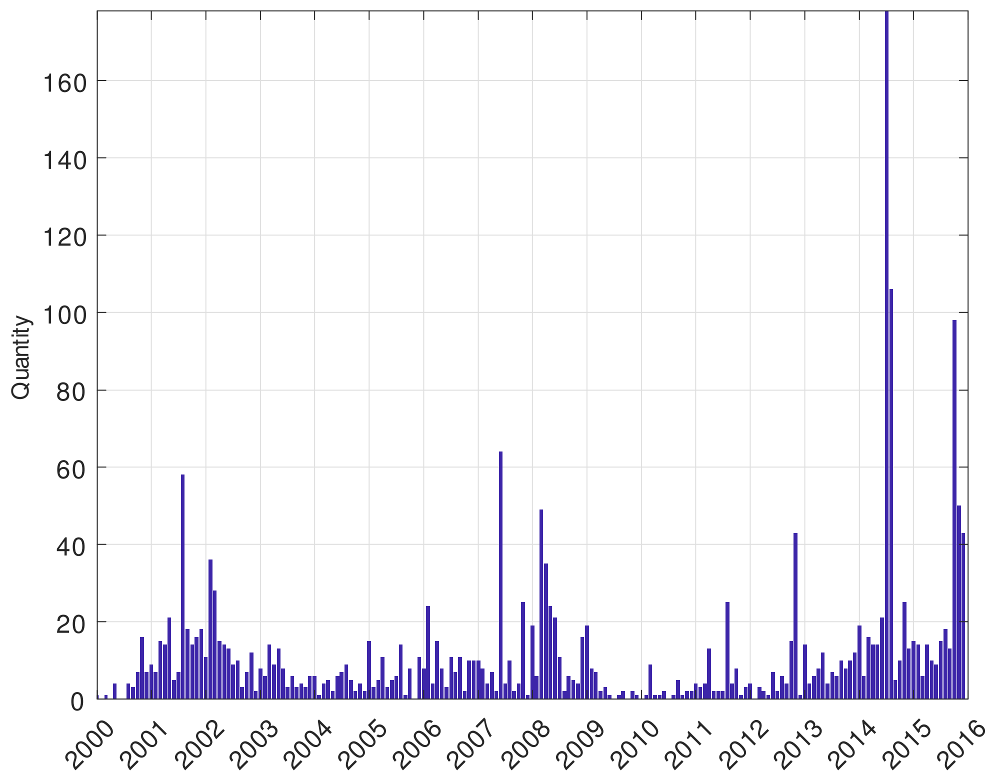


Figure 1: Number of terrorist attacks in Israel between 2000 and 2016. Source: National Consortium for the Study of Terrorism and Responses to Terrorism (START). Global Terrorism Database.

The psychological effects on expectations and feelings of uncertainty might be considerable, giving our study the unique ability to assess the impact of uncertainty, rather than the unforeseen effects of negative shocks (Romanov et al., 2012).

In this study, we use three sources of statistics on terrorist attacks to measure terrorism in Israel, each including four different indicators: number of people killed during terrorist attacks, number of people wounded during terrorist attacks, total number of casualties (killed and wounded) during terrorist attacks, and total number of terrorist attacks. We use one academic source (Global Terrorism Database,[7] hereafter GTD) and two government sources (Ministry of Foreign Affairs, hereafter MFA, and the National Insurance Institute,[8] hereafter NII). The number of terrorist attacks is not

[7] Database supported by the University of Maryland and maintained by the National Consortium for the Study of Terrorism and Responses to Terrorism (START).

[8] Which—among other tasks—provides social security services in Israel.

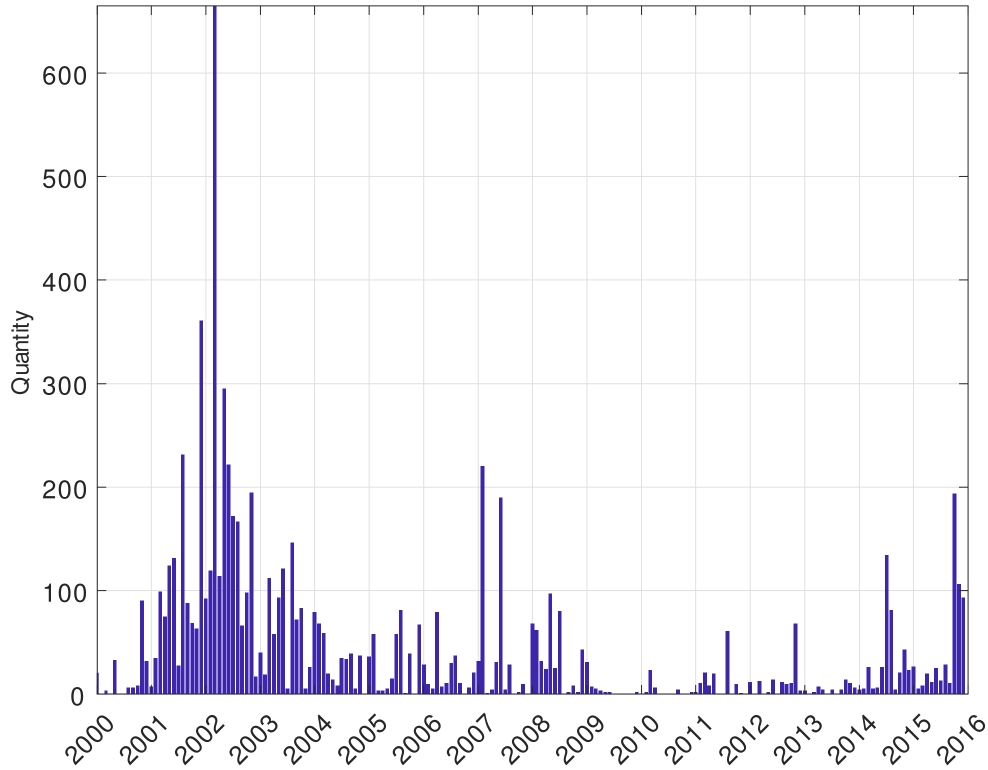


Figure 2: Number of killed and wounded during terrorist attacks in Israel between 2000 and 2016. Source: National Consortium for the Study of Terrorism and Responses to Terrorism (START). Global Terrorism Database.

available in the MFA data.

These sources have their own methodology to account for terrorist attacks and casualties.

GTD data are generated by isolating an initial pool of potentially relevant articles and then using sophisticated natural language processing (NLP) and machine learning techniques to further refine the results, remove duplicate articles, and identify possibly relevant articles. The GTD team manually reviews this second subset of articles to identify unique events that satisfy the GTD inclusion criteria and subsequently researches and codes them according to GTD specifications. GTD data are reported separately for Israel (within the 1967 borders) and Gaza and the West Bank. To achieve better comparability, in particular with the MFA data, and to account for the fact that most attacks in Gaza and the West Bank target Israelis, we aggregate the two datasets. However, tests conducted with only Israel (within the 1967 borders) terrorism data lead to similar results.

MFA data are from the chronology of terrorist attacks in Israel published by the Israeli Ministry of Foreign Affairs and collected by Johnston (2016). MFA data include the West Bank and Gaza in their definition of Israel.

NII data are from the national social security services. These data include terrorist attacks involving Israelis all over the world, without geographical distinction. That is, contrary to our other sources (GTD and MFA), terrorist attacks outside Israel are considered.

Although during periods of high terrorism, there were months with very few or no terrorist casualties or attacks (e.g., February and July 2003 saw roughly 10 people injured at a time when most months saw figures going into the hundreds), we use a backward-looking (12 months) moving average for all terrorism indicators because financial data and turmoil are inherently persistent. The moving average accounts for high volatility by correctly identifying the respective months as part of periods with high instability.

2.2 Market and expert forecasts

Israel is the only highly developed country with sound economic institutions and fully developed financial markets (and thus access to very detailed economic information) to have experienced a long history of terror. Particularly interesting for us are market expectations and professional forecasts. Since Israel issues both inflation-indexed and non-indexed bonds, it is straightforward to compute market expectations of inflation (breakeven inflation rates).

As a measure of professional forecasts, we use the combined professional forecast assembled by the Bank of Israel.

Expert as well as market-based inflation and exchange-rate forecasts are essential when formulating the inflation-targeting monetary policy of a small open economy. Thus, the Bank of Israel collects an excellent set of forecasts that are updated regularly.[9]

In line with this practice of the Bank of Israel, we use the forecasts as given without further risk adjustment. Although this implies that our measures are not perfect measures of expectations, it guarantees that they are perfect measures of policymakers' perception of expectations, which is more essential. However, we do control for inflation risk and exchange-rate risk to ensure that our results are not driven by lack of risk adjustment.[10]

In this study, we use two types of market-based 1-year (1Y) consumer price index (CPI) inflation forecasts used by the Bank of Israel's Monetary

[9] See, for example, publicly available minutes related to interest rate policy decisions. The first section, related to inflation, as well as almost all staff forecasts, mention expert and market-based forecasts.

[10] See below and Section 4.1 for more details about the inflation risk premium.

Policy Committee (MPC): the 1Y Forward (contract) implied inflation forecast and the 1Y Breakeven (zero-coupon bond implied) inflation forecast. The first is the instantaneous 1Y forward inflation rate, and the second is reported by the Bank of Israel as the *official* 1Y market-based inflation forecast.[11] These time series are not transformed and used as they are in the MPC.

In addition, the Bank of Israel collects a series of forecasts provided by professional forecasters, giving an excellent overview of the professional inflation expectations. Contrary to many other surveys, individual forecasters are not asked for their opinions at a given point in time, but they are able to update their forecasts at will, thereby essentially giving us daily data on professional forecasts. Expert forecasts used in this study are computed as the simple arithmetic mean of the inflation forecasts of commercial banks and economic consulting companies. This measure, as well as the 1Y Breakeven inflation forecast, are reported in official publications of the Bank of Israel.[12]

The situation is equally good for exchange rates. There is an active future ILS/USD market that allows us to infer market expectations for the exchange rate. Given their importance, exchange rates are covered by the Bank of Israel's in-house survey of forecasters.[13]

The forecasts are obtained for the last day of the month. Variables used to explain forecast performance are from the month when the forecast is made. Thus, they can affect the forecast and do not just appear as a forecast error by occurring after the forecast is made.

A detailed description of the performance of the inflation and exchange rate forecasts is provided in Sections 4.1 and 4.2, respectively.

[11] This measure is assumed to deal with several inherent breakeven inflation problems. It considers the small number of real bond series, bias derived from the indexation mechanism (indexation lags and other mechanisms impacting the calculation of the yield to maturity of the CPI indexed bonds), and CPI seasonality affecting the pricing of CPI-indexed bonds. However, inflation risk premiums as well as bias derived from differences in taxation and liquidity between different bond types are not considered.

[12] Every month, the Bank of Israel publishes a press release. Its section on monetary policy and inflation (data and reports) details the expected rate of inflation derived from various sources.

[13] The final variable, for which implicit market forecasts exist, are interest rates, whose expectations can be computed from the yield curve. However, the survey of professional forecasters covers the policy rate by the Bank of Israel. Nonetheless, the expectation on interest rates from Israeli treasury bills, implied by the term structure, constitutes an implicit forecast for the treasury bill rate. While close to each other, the two interest rates (policy rate and treasury bill rate) are not precisely the same. In addition, the nominal interest rate did not change significantly since 2014, while other indicators (terrorism and control variables detailed in the next section) changed drastically. Therefore, we exclude the nominal interest rate from our study.

2.3 Further control variables

Market expectations and professional forecasters could respond to financial uncertainty.[14] Then, we employ three different measures of volatility to serve as control variables. First, we use the monthly standard deviation of daily returns (approximated as log differences) of the relevant stock market index, that is, the TA-100 index, which is one of the broadest leading indexes in the Tel Aviv Stock Exchange.[15] Second, we include the spread between the highest and lowest levels of this index within the month of the forecast. Third, we consider the monthly average of the corresponding daily spreads. While the monthly spread reacts more strongly to major movements within a month, the average daily spread implicitly gives higher weight to intraday fluctuations.

Fig. 3 shows that the highest financial uncertainty was reached during and around the Lehman Brothers' collapse (2008Q3–Q4) and the European and Greek debt crises (2010Q1, 2011Q2–Q3, and 2015Q3). Volatility was also high during most of the Second Intifada period (2000Q1–2004Q1) and the (unanticipated) elections for the 18th Knesset held in 2009Q1.

In addition, since terrorism in Israel might be related to unrest in the Middle East as a whole, which has serious repercussions for the price of oil, a major factor in global economic development, we control for commodity price volatility. More precisely, in our empirical analysis, we control for the monthly volatility (standard deviation of daily log differences) of crude oil,[16] natural gas,[17] and CRB commodity price index[18] expressed in ILS and USD (Fig. 4).

Finally, we control for the volatility of the USD/ILS exchange rate, again computed as the standard deviation of daily log differences over one month.

[14] The global financial crisis and subsequent recovery period provided new insights about forecast evaluation during the period of data instability in both the Eurozone (Benchimol and Fourçans, 2017) and the United States (Caraiani, 2016), as well as in Israel (Benchimol, 2016).

[15] The TA-100 index consists of 100 shares with the highest market capitalization and includes the TA-25 and TA-75 indexes.

[16] West Texas Intermediate (WTI) crude oil spot price, US dollars per barrel, not seasonally adjusted.

[17] Henry Hub natural gas spot price, US dollars per million British Thermal Unit (BTU), not seasonally adjusted.

[18] Thomson Reuters Core Commodity Commodity Research Bureau (CRB) index.

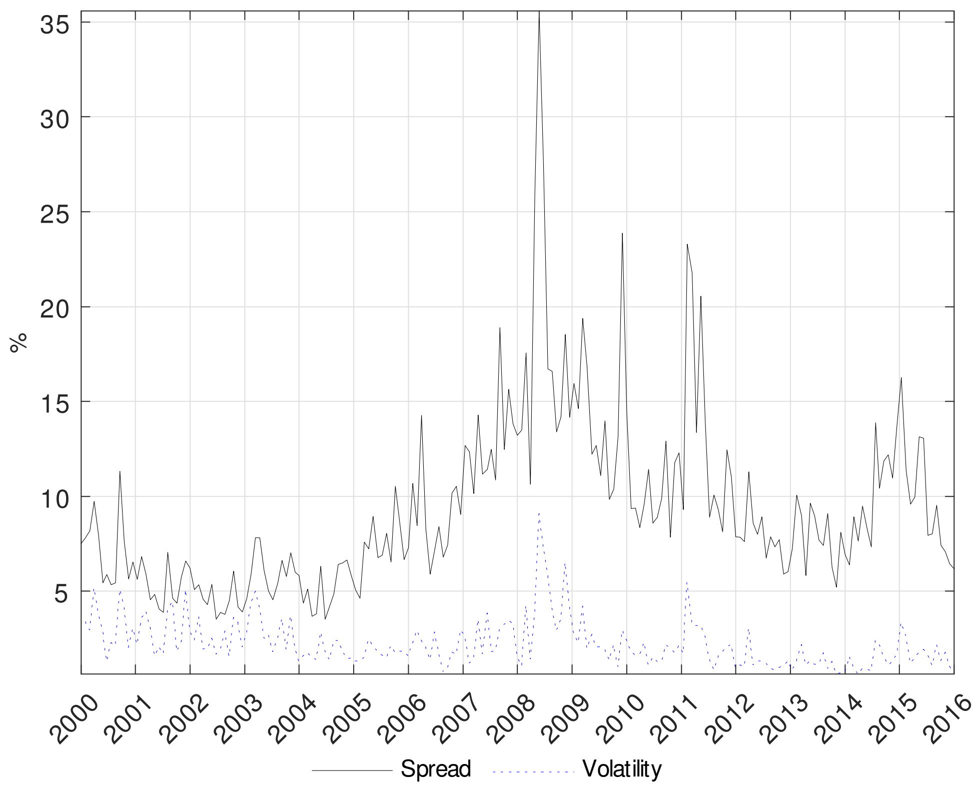


Figure 3: Financial uncertainty measured as the TA-100's one-month rolling window volatility (standard deviation) and daily spread (high-low spread) between 2000 and 2016.

3 Methodology

While early literature on forecast evaluation usually evaluated forecast performance for the entire sample, the past decade has seen the emergence of literature on forecast evaluation in unstable environments, which allows accounting for situations such as those described in Section 2. These new tests allow us to assess time variation in both the performance of individual forecasts and relative performance of forecasts, as well as to account for the fact that some models and/or forecasters might shine in some situations, but not in others.

Some tests involved are essentially supremum versions of established tests over a rolling window of forecasts. This introduces a multiple testing problem that causes the critical values of those tests to be much higher than those of the underlying individual tests. If there is no fluctuation, this of course causes an unnecessary loss in power. Thus, the tests are often accompanied

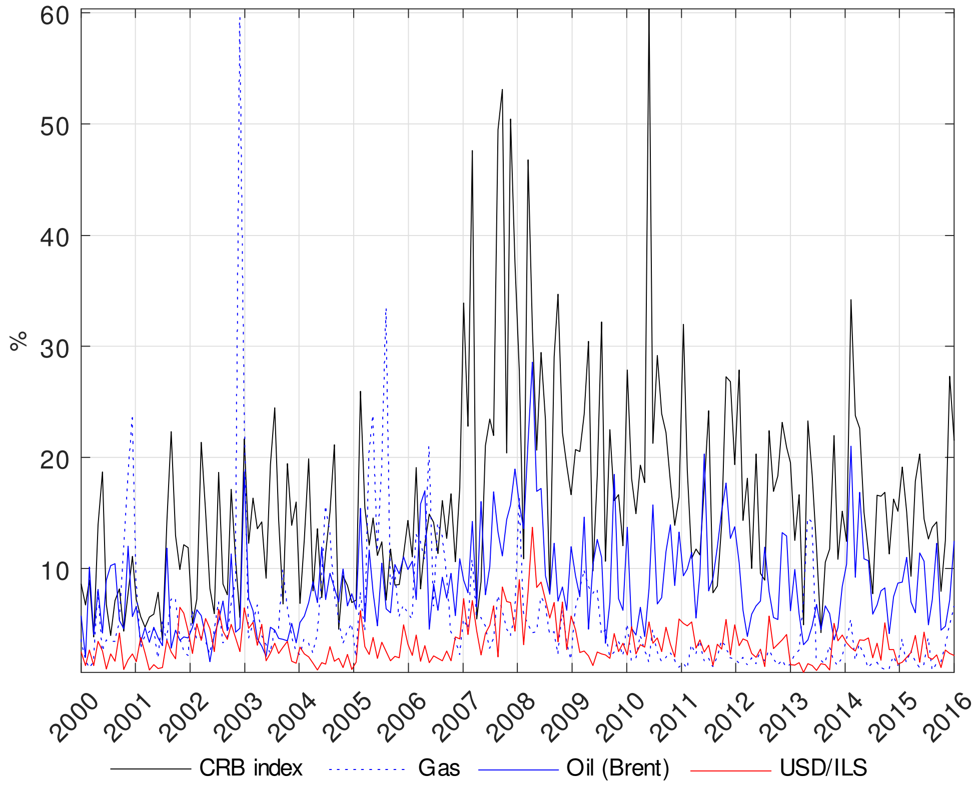


Figure 4: Financial uncertainty measured as the one-month rolling window volatility (standard deviation) of the CRB index, gas and oil prices in ILS, and the USD/ILS exchange rate between 2000 and 2016.

by full sample versions. However, since most of our results indicate strong rejection, we omit reporting these full sample tests in this paper.

3.1 Unbiasedness in unstable environments

We start the analysis with the most fundamental question, that is, whether the forecasts we consider are unbiased. Rossi and Sekhposyan (2016) suggested using the maximum of rolling-window Wald-type unbiasedness tests as the test statistic. Thus, the null hypothesis is that the forecast under consideration is rational at any point in time during the sample. Rejection does not imply that a forecast is permanently biased, but that it was biased at least once during the sample period. Following the original research, we report the entire time series of underlying individual test statistics to obtain a visual representation of which periods cause the rejection. We apply the same strategy for other related tests.

The underlying test statistic is based on a standard Mincer and Zarnowitz (1969) regression:

$$y_{t+h} = \alpha + \beta \hat{y}_{t+h,t} + \eta_{t,h} \tag{1}$$

where y_{t+h} is the variable of interest at $t+h$, $\hat{y}_{t+h,t}$ is the corresponding forecast made at time t, and $\eta_{t,h}$ is the residual of the test regression. The traditional test for unbiasedness examines the joint hypothesis that $\alpha = 0$ and $\beta = 1$. It is straightforward to observe (as pointed out, for example, by West and McCracken (1998)) that this can be rearranged so that the h step-ahead forecast error at time t, $\hat{v}_{t,h} = y_{t+h} - \hat{y}_{t+h,t}$, becomes the left-hand side variable:

$$\hat{v}_{t,h} = \theta_0 + \theta_1 \hat{y}_{t+h,t} + \eta_{t,h}, \tag{2}$$

where θ_0 and θ_1 are the regression coefficients of the adjusted test equation.[19]

This gives us the more approachable null hypothesis $\theta = [\theta_0,\ \theta_1] = \mathbf{0}$, which can be easily assessed with a standard Wald test using the test statistic:

$$\mathcal{W} = \hat{\theta}\hat{\Omega}^{-1}\hat{\theta}', \tag{3}$$

where $\hat{\theta}$ is the estimator of θ and $\hat{\Omega}$ is the corresponding heteroscedasticity and autocorrelation consistent (HAC) robust estimator of the covariance matrix of θ.[20]

With a sample of P forecasts and using window length m, the proposed test statistic takes the following form:

$$\max_{j \in \{m,\ldots,P\}} \mathcal{W}_{j,m} \tag{4}$$

Because of the rolling-window nature of the underlying individual Wald tests, the distribution of this test statistic under the null hypothesis asymptotically converges to a function of Brownian motions. The precise distribution depends on whether the uncertainty in the parameter estimates in the forecasting model itself should be accounted for (i.e., not the uncertainty concerning θ but the degree of uncertainty in the parameters used to generate $\hat{y}$). In the case of expert or market-based forecasts, the so-called model-free

[19]That is, $\theta_0 = \alpha$ and $\theta_1 = \beta - 1$.

[20]Since it is well established that η follows an $MA(h)$ process even for perfectly rational and efficient forecasts due to overlapping unforeseeable shocks over the h periods of the forecast, an HAC correction using a sufficiently high lag order is of utmost importance when not explicitly modeling this moving average behavior. In this study, we follow the suggestion of Rossi and Sekhposyan (2016) and use a standard Newey and West (1987) estimator for the covariance matrix. We use 25-month windows in the kernel for our HAC variance estimators (12 months on both sides), which is above what rules-of-thumb usually suggest. This should suffice to correct the degree of MA introduced by overlapping forecasts.

forecasts, the distribution under the null collapses to its most simple form, depending asymptotically only on m/P and not the sample size used to produce forecasts.

3.2 Stability of relative forecast performance

3.2.1 Fluctuation test

Much like the test for unbiasedness in unstable environments is a maximum of individual unbiasedness test statistics over a rolling window, the test for relative forecast performance in unstable environments proposed by Giacomini and Rossi (2010) is the maximum of traditional relative forecast performance tests over a rolling window.

Similar to the previous test, the null hypothesis is that the forecasts under consideration perform equally well at any point in time. Exceeding the critical value does not imply that one model constantly outperforms the other, but merely that there is a meaningful difference in the predictive ability for a subsample.

More precisely, the test statistic is the maximum of local Diebold and Mariano (1995) test statistics, in which the variance estimator is based on the full sample of forecasts, rather than the individual window for which the mean difference in predictive ability is computed. Since the full sample estimator is used in this approach, m can be much smaller than in the previously outlined test. This is because the rationality test needs m to be sufficiently large to allow meaningful estimation of Ω, which corresponds to σ in this test, within the rolling window, which is not relevant here. Denoting the loss function for the two forecasts under consideration at time t by $L_{1,t,h}$ and $L_{2,t,h}$ and the corresponding loss difference by $\Delta L_{t,h} = L_{1,t,h} - L_{2,t,h}$, we can write the test statistic as

$$\max_{j \in \{m,\ldots,P\}} \left| \hat{\sigma}^{-1} m^{1/2} \sum_{t=j-m/2}^{j+m/2-1} \Delta L_{t,h} \right| \tag{5}$$

where $\hat{\sigma}$ is the HAC robust estimator of the standard error of the mean of $\Delta L_{t,h}$. Again, the critical values are, asymptotically, functions of Brownian motions. Since the finite sample bias in the test for unbiasedness under instability is mostly introduced by the uncertainty in the estimation of Ω over m observations, the finite sample problems are far less pronounced in this test, and we use the asymptotic critical values provided by Giacomini and Rossi (2010).

The test we use is two sided, because there is no valid prior assumption on the superiority of one forecast over another. For the visual interpretation, we report that $\hat{\sigma}^{-1}m^{1/2}\sum_{t=j-m/2}^{j+m/2-1}\Delta L_t$, rather than the corresponding absolute, which is part of the test-statistic, to observe whether the rejection is driven by forecast 1 or 2 to be superior during a subsample.

3.2.2 One-time reversals in forecast performance

Often, a potential change in forecast performance is due to a single structural break (e.g., introduction of a new forecasting model or policy that is not well understood by one forecasting agent), rather than fluctuations over time. In this case, the very flexible framework outlined above still creates an unnecessary loss in power, compared with a test that explicitly models a single structural break.

Thus, Giacomini and Rossi (2010) proposed a so called one-time reversal test, which follows the spirit of the supremum structural break tests introduced by Hawkins (1987).

Technically, the test includes a testing procedure composed of three separate tests.

The first test statistic is a straightforward full sample test:

$$LM_1 = \hat{\sigma}^{-2}P^{-1}\left[\sum_{t=1}^{P}\Delta L\right]^2 \tag{6}$$

The second is the actual structural break statistic based on the loss differences in various subsamples:

$$LM_2 = \max_{j\in\{0.15P,\ldots,0.85P\}} LM_2\left(j\right) \tag{7}$$

where

$$LM_2\left(j\right) = \hat{\sigma}^{-2}P^{-1}\left(j/P\right)^{-1}\left(1-j/P\right)^{-1}\left[\sum_{t=1}^{j}\Delta L-\left(j/P\right)\sum_{t=j+1}^{P}\Delta L\right]^2 \tag{8}$$

Finally, the joint test-statistic with the null hypothesis of equal performance at any point in time is as follows:

$$\phi = LM_1 + LM_2 \tag{9}$$

Correspondingly, if the third test statistic is rejected, we can reject equal performance at every point in time. Only then do we assess the individual underlying statistics LM_1 and LM_2. If only LM_1 is rejected, this indicates the permanent superiority of one model. If only LM_2 is rejected, this indicates the reverse, in which one model is superior only for a certain subsample. If both tests are rejected, then the interpretation is not as clear cut, but it generally implies some change in relative performance that is not strong enough to affect the relative order of forecasts. If there is evidence of a structural break, the most likely breakpoint is $j^* = \underset{j\in\{0.15P,\ldots,0.85P\}}{\operatorname{argmax}} LM_2(j)$.

3.3 Encompassing in unstable environments

Even if one forecast is permanently or temporarily better, this does not necessarily imply that the superior forecast fully exploits the available information at all times. Thus, we move to the next step and test the forecast encompassing in the same framework, proposed by Giacomini and Rossi (2010), which we used to assess rationality.

The key difference is that the equation underlying the Wald test changes to a standard encompassing equation given by

$$\hat{\upsilon}_{1,t,h} = \theta_0 + \theta_1 \left(\hat{\upsilon}_{1,t,h} - \hat{\upsilon}_{2,t,h}\right) + \eta_{t,h} \tag{10}$$

where $\hat{\upsilon}_{1,t,h}$ and $\hat{\upsilon}_{2,t,h}$ are the forecast errors of models 1 and 2, respectively.

Contrary to the test for unbiasedness, we are merely interested in θ_1. Thus, the individual Wald statistics collapse to

$$\mathcal{W} = \hat{\theta}_1 \hat{\omega}^{-1} \hat{\theta}_1 \tag{11}$$

where $\hat{\omega}$ is the lower right element of $\hat{\Omega}$ and $\hat{\theta}_1$ is the estimator of θ_1.

3.4 Conditional relative performance

After exploring time variation in forecast performance and, more importantly, relative performance, we now assess the reasons for the variation. To that end, we employ the test for conditional forecast performance proposed by Giacomini and White (2006).

Denoting the set of conditions that potentially explain the difference in performance at time t by row vector h_t, the test statistic is once again a Wald-type statistic given by

$$T = P\left(P^{-1}\sum_{t=1}^{P} h_t \Delta L_{t,h}\right)\hat{\Omega}\left(P^{-1}\sum_{t=1}^{P} h_t \Delta L_{t,h}\right)' \tag{12}$$

This statistic is a standard Wald statistic in which the individual coefficients are bilateral correlations between the elements of h_t and ΔL. $\hat{\Omega}$ is the corresponding HAC robust estimator of the covariance matrix. The test statistic follows a simple χ^2_q distribution, in which q is the number of elements in h_t.

The null hypothesis is that forecast performance is not related to any indicator collected in h_t. The explanatory variables are usually, and in our example, measured at time t rather than at $t + h$; that is, we do not assess which kind of shock at $t + h$ is unforeseeable for certain forecasters, but we assess conditions at t when the forecast is made. To a certain degree, this allows us to choose the preferred forecast, ex ante, that is, when the forecast is made, rather than later when the realization is known.

It must be noted that including several indicators in h_t does not "control" for indicators in the sense of regression analysis, since the coefficients are simple bilateral correlations rather than regression coefficients. However, we also want to assess whether terrorism truly has an impact that is not related to financial market uncertainty. Nonetheless, due to the aforementioned construction, performing a Wald test on only one coefficient estimated jointly with others merely yields a result that is obtained when testing this individual explanatory variable without controlling for further indicators.

Therefore, we also run an ad hoc variation of this test, in which we use regression coefficients rather than correlation coefficients and the corresponding covariance matrix, and we run a Wald test on the coefficient(s) of interest only.

4 Results

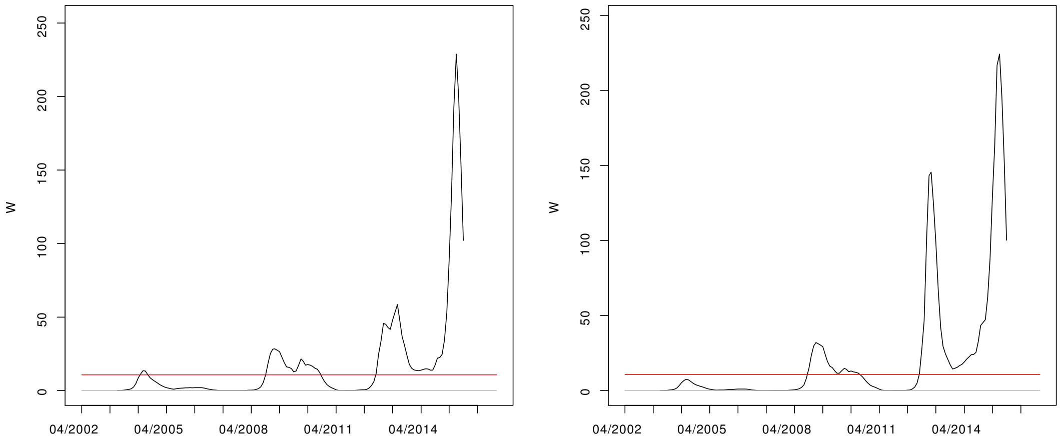
This section presents the results for tests related to the CPI inflation and the USD/ILS exchange rate, as well as expert and market-based forecasts.

4.1 Inflation

Unbiasedness Our test for unbiasedness in unstable environments strongly rejects both expert forecasts and market-implied inflation expectations (Fig. 5).

Since the null hypothesis of the underlying test is that the forecast is always unbiased, this does not imply a bias on average or even for majority of the periods. A visual inspection of the time series of the individual Wald statistics that underlie the (supremum) test statistic used indicates that, in both cases, the rejection is primarily driven by a strong bias between 2008Q4 and 2010Q3, and following 2012Q4.

The earlier of the two periods corresponds to both substantial fears (Operation Cast Lead, 2008Q4–2009Q1, and unanticipated Israeli legislative elec-



(a) Expert forecast

(b) Market-based forecast

Figure 5: Unbiasedness test (CPI inflation). Confidence interval: 5%.

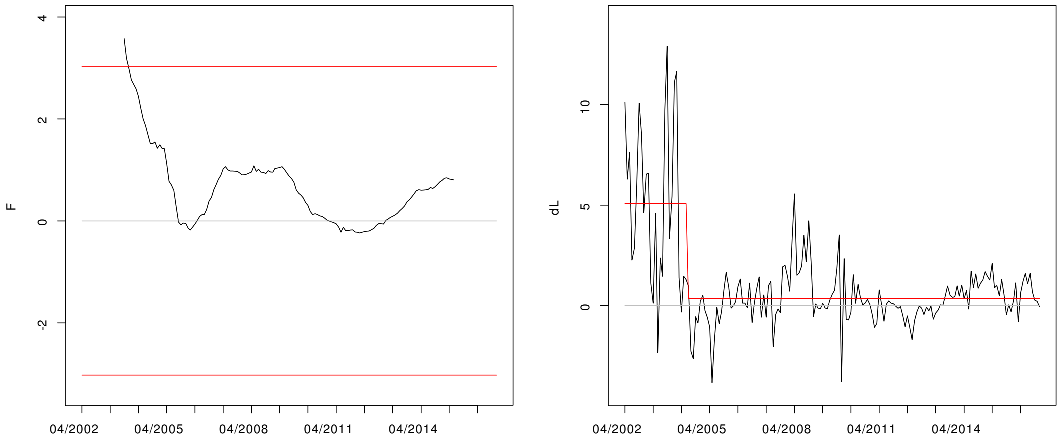
tions, 2009Q1) and financial uncertainty until 2010Q3, while the second period after 2012Q4 is mainly related to warfare instability (Operation Pillar of Defense, 2012Q4, and Operation Protective Edge, 2014Q3). Furthermore, the underlying Wald statistics pick up some movement during the highest violence level of the Second Intifada (2004Q1–Q2). However, these movements would be sufficient for rejection by expert forecasts based on this period alone.

Even this preliminary evidence, based on rationality tests, lends quite strong support to our main hypothesis; that is, uncertainty and instability of any form, whether financial or—as in the unfortunate case of Israel—caused by terrorism, strongly affects expectations and thereby forecasts.

Relative forecast performance and encompassing Both expert and market-based inflation forecasts are strongly affected by uncertainty, and the order of magnitude seems similar. Although a fluctuation test that assesses the null hypothesis of equal forecast performance at any point in time is rejected, this rejection is exclusively driven by the early period of the sample, when expert surveys hugely outperformed market expectations. Fig. 6 shows development of the underlying individual test statistics over time, indicating another extended period of superior survey forecasts in the second half of the 2000s; however, the test statistics are far below the critical value.[21] At other

[21] Tests reported in Fig. 6 use squared forecast errors as a loss function. Performance differences are defined as market-based loss less expert-based (survey) loss. Thus, high

times, the performance of both forecasts is essentially identical.



(a) Fluctuation test

(b) One-time reversal test

Figure 6: Fluctuation and one-time reversal tests (CPI inflation). Confidence interval: 5%.

Those prolonged but insignificant fluctuations in relative performance correspond to periods of fear (Second Lebanon War and victory of Hamas in the Palestinian legislative elections of 2006 as well as Palestinian Gaza-based mortar attacks and Israeli missile strikes during 2011–2013); however, the results by themselves are not sufficient to prove our uncertainty hypothesis.

The magnitude of the fluctuations is small enough that we cannot rule out a single structural break in relative forecast performance around 2004, as indicated by the one-time reversal test.

The encompassing test (Fig. 7) paints a clearer picture.

Again, we clearly reject that the typically superior survey forecasts encompass market forecasts. These rejections are essentially driven by the very same periods that drive the results of our rationality test. That is, while both experts and market participants are strongly affected by uncertainty, they are affected in very different ways, which leads to the natural follow-up question: can uncertainty indeed explain the differences in forecast performance?

Conditional relative forecast performance The core question in our study is whether terrorist attacks affect the (relative) performance of expert

values of the test statistic indicate worse performance of market-based forecasts and corresponding superiority of the expert forecasts.

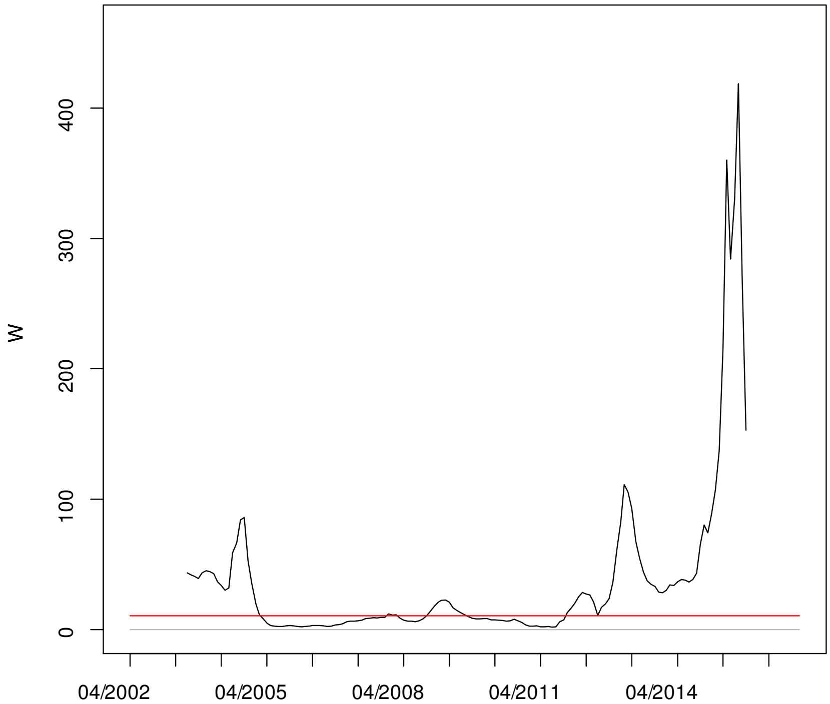


Figure 7: Encompassing test (CPI inflation). Confidence interval: 5%.

and market-based forecasts. All indicators of terrorism we use turn out to be significant at the 5% level.[22]

To assess the robustness of those results, beyond the inclusion of a range of different indicators, we test specifications controlling for the alternative reasons for time-varying forecast performance that might be correlated to terrorism.[23] First, we include several indicators of financial stability (Fig. 3). Terrorism might cause market turbulence that in turn affects economic forecasts, just as financial turmoil might do when caused by any other source.

[22]In addition to the standard model, we run an extended model in which we account for potential non-linearity by including the square of the terror term. In cases in which we find a significant square term, it is combined with a highly significant coefficient on the level. That is, there is some evidence that the impact of terror on forecast performance declines quickly. In other words, the existence of terror rather than its degree affects forecast performance. However, those results are far from robust and strongly depend on the selection of the terror indicator. Therefore, we opt to exclude said non-linearity from our baseline specification. More detailed results are available upon request.

[23]As a robustness check, we also conducted this exercise with terrorism data excluding terrorism in Gaza and the West Bank, thus using only GTD measures (data on Israel without Gaza and the West Bank). Our results lead to similar conclusions as presented below. These results are available upon request.

Second, we include commodity price volatility as well as USD/ILS volatility. Since terrorism in Israel might be related to instability in the Middle East, where several main producers of oil are located, there might be a relationship between inflation forecasts and commodity prices volatility. The latter are known to have a major influence on world economy and, specifically, on Israel, which is a small open economy and was an oil and gas importer before developing its own natural gas resources.

Tables 1 and 2 present detailed results of conditional predictive ability tests (CPA) when considering the joint test of both market and expert inflation forecasts against control variables.[24]

All our indicators of terrorism are individually significant. In particular, we find that market forecasts deteriorate more strongly in times of high terrorism compared with expert forecasts. As mentioned in Section 3, the test proposed by Giacomini and White (2006) does not control for multicollinearity even when including several variables simultaneously. However, our modified test, which relies on regression coefficients rather than correlations for the underlying Wald test statistics, still rejects indicators for terrorism after including financial uncertainty, USD/ILS, or commodity price changes as control variables. The only exception is the number of attacks, as measured by GTD, since in most cases, we find significance for neither the number of attacks nor the additional control, but we do find individual significance for the number of attacks, without additional controls, and joint significance. We achieve the best results when using NII indicators, particularly—and surprisingly—the number of attacks as measured by NII.

Most alternative indicators of uncertainty, that is, financial indicators and commodity prices, seem to play a role when assessed individually, but they are not that robust. While we find that most indicators still seem significant for some terrorism indicators, those results are not stable and strongly depend on the terrorism indicator chosen. The only exception is gas price volatility, which remains significant in all regressions. However, in all those cases, the corresponding terrorism indicator is still significant, again with the exception of the number of attacks, as reported by GTD. Based on the overwhelming robustness of our findings for 10 out of 11 terrorism indicators, we find fairly strong evidence that terrorism matters for relative forecast performance.[25]

It seems plausible that the number of terrorist attacks, as measured by

[24] A detailed description of control variables representing financial instability (volatility and spreads) is provided in Section 2.3.

[25] Other results are available upon request. These tests were conducted for the price levels and volatilities of both ILS and USD, as well as while considering a moving average (12 months) for the control variable. All results confirm that terror is the best explanatory variable of inflation forecasts errors.

		Inflation forecasts (1Y)								
		GTD			*MFA*			*NII*		
Terror	Control variable	CPA	terror	control	CPA	terror	control	CPA	terror	control
Killed		0.02			0.01			0.02		
	TA-100 vol.	0.03	1.34	2.47	0.03	1.92	2.34	0.03	1.32	2.46
	TA-100 spread	0.03	2.87	0.85	0.02	3.33	1.07	0.03	2.94	1.03
	USD/ILS vol.	0.03	2.23	0.82	0.03	2.93	0.95	0.04	2.47	0.96
	Oil* vol.	0.03	1.41	2.51	0.03	1.75	2.29	0.04	1.14	2.43
	Gas* vol.	0.04	1.93	2.12	0.03	2.57	1.82	0.04	1.70	2.05
	CRB* vol.	0.03	3.02	1.64	0.03	3.21	1.60	0.03	2.80	1.63
	Oil vol.	0.03	1.54	2.22	0.03	2.32	2.14	0.04	1.48	2.21
	Gas vol.	0.04	1.93	2.14	0.03	2.58	1.86	0.04	1.71	2.08
	CRB vol.	0.03	2.52	1.20	0.03	2.98	1.26	0.03	2.61	1.32
Wounded		0.01			0.01			0.01		
	TA-100 vol.	0.03	1.86	2.32	0.03	1.81	2.37	0.02	3.01	2.72
	TA-100 spread	0.03	3.18	0.99	0.03	3.29	1.07	0.02	3.02	0.84
	USD/ILS vol.	0.03	2.70	0.82	0.03	2.88	0.95	0.02	2.98	0.84
	Oil* vol.	0.03	2.02	2.34	0.03	1.64	2.32	0.02	1.97	2.48
	Gas* vol.	0.04	2.66	2.09	0.03	2.45	1.87	0.02	2.50	1.89
	CRB* vol.	0.03	3.06	1.63	0.03	3.18	1.61	0.02	3.20	1.62
	Oil vol.	0.03	2.35	2.11	0.03	2.16	2.15	0.02	2.38	2.26
	Gas vol.	0.04	2.68	2.11	0.03	2.46	1.90	0.02	2.49	1.91
	CRB vol.	0.03	2.83	1.20	0.03	2.94	1.27	0.02	2.89	1.14
Total		0.01			0.01			0.01		
	TA-100 vol.	0.03	1.78	2.35	0.03	1.81	2.37	0.02	2.90	2.66
	TA-100 spread	0.03	3.21	0.97	0.03	3.29	1.07	0.02	3.24	0.91
	USD/ILS vol.	0.03	2.68	0.82	0.03	2.88	0.95	0.02	3.13	0.86
	Oil* vol.	0.03	1.93	2.38	0.03	1.64	2.32	0.02	1.97	2.43
	Gas* vol.	0.04	2.61	2.10	0.03	2.45	1.87	0.03	2.62	1.89
	CRB* vol.	0.03	3.10	1.64	0.03	3.18	1.61	0.02	3.39	1.64
	Oil vol.	0.03	2.23	2.13	0.03	2.16	2.15	0.02	2.42	2.22
	Gas vol.	0.04	2.63	2.12	0.03	2.46	1.90	0.03	2.61	1.91
	CRB vol.	0.03	2.84	1.20	0.03	2.94	1.27	0.02	3.07	1.17
Number		0.02						0.01		
	TA-100 vol.	0.09	1.14	2.86				0.05	3.45	2.31
	TA-100 spread	0.09	0.67	0.47				0.05	3.93	1.09
	USD/ILS vol.	0.08	0.34	0.77				0.05	3.52	0.66
	Oil* vol.	0.08	0.06	2.84				0.05	2.68	1.63
	Gas* vol.	0.04	0.69	2.21				0.04	3.68	1.82
	CRB* vol.	0.09	0.94	1.52				0.05	4.10	1.73
	Oil vol.	0.07	-0.38	2.52				0.05	2.76	1.50
	Gas vol.	0.04	0.70	2.23				0.04	3.67	1.80
	CRB vol.	0.08	0.40	1.12				0.05	3.51	0.96

Table 1: Breakeven and expert inflation forecasts predictive ability tests. CPA is the p-value of the conditional predictive ability test. *terror* is the t-test of the terror variable considered. *control* is the t-test of the control variable considered. A positive t-test means that expert forecasts are better than market-based ones. A negative t-test means the opposite. $Total$ is the sum of those killed and wounded, and $Number$ is the quantity of terrorist attacks. Variables with $*$ are in USD.

		Inflation forecasts (1Y)								
		GTD			*MFA*			*NII*		
Terror	Control variable	CPA	terror	control	CPA	terror	control	CPA	terror	control
Killed		0.05			0.06			0.05		
	TA-100 vol.	0.01	3.01	0.50	0.01	2.61	0.68	0.01	2.76	0.58
	TA-100 spread	0.00	3.05	-0.37	0.00	2.69	-0.02	0.00	2.86	0.18
	USD/ILS vol.	0.00	3.08	-1.30	0.00	2.62	-0.72	0.00	2.76	-0.64
	Oil* vol.	0.04	2.99	0.25	0.04	2.59	0.21	0.04	2.75	0.15
	Gas* vol.	0.08	3.03	2.26	0.08	2.56	2.10	0.08	2.74	2.07
	CRB* vol.	0.01	3.01	-0.62	0.01	2.63	-0.74	0.01	2.77	-0.63
	Oil vol.	0.03	2.97	0.40	0.03	2.59	0.46	0.03	2.75	0.46
	Gas vol.	0.08	3.02	2.29	0.07	2.55	2.14	0.07	2.73	2.12
	CRB vol.	0.00	3.05	-0.88	0.00	2.64	-0.45	0.00	2.78	-0.35
Wounded		0.04			0.04			0.01		
	TA-100 vol.	0.01	3.35	-0.16	0.01	3.08	0.20	0.02	2.62	1.40
	TA-100 spread	0.00	3.40	-0.24	0.00	3.16	-0.11	0.00	2.59	-0.96
	USD/ILS vol.	0.00	3.41	-1.49	0.00	3.10	-0.90	0.01	2.54	-1.35
	Oil* vol.	0.04	3.30	-0.08	0.04	3.06	-0.09	0.03	2.54	0.29
	Gas* vol.	0.08	3.40	2.20	0.08	3.06	1.80	0.05	2.47	1.91
	CRB* vol.	0.01	3.34	-1.10	0.01	3.10	-1.19	0.01	2.56	-1.31
	Oil vol.	0.03	3.26	0.12	0.03	3.05	0.32	0.02	2.56	0.55
	Gas vol.	0.08	3.40	2.26	0.08	3.05	1.86	0.05	2.45	1.96
	CRB vol.	0.00	3.38	-1.18	0.00	3.11	-0.89	0.01	2.58	-1.42
Total		0.04			0.04			0.01		
	TA-100 vol.	0.01	3.31	-0.03	0.01	3.04	0.27	0.02	2.77	1.31
	TA-100 spread	0.00	3.36	-0.25	0.00	3.12	-0.05	0.00	2.75	-0.76
	USD/ILS vol.	0.00	3.37	-1.45	0.00	3.05	-0.86	0.01	2.71	-1.26
	Oil* vol.	0.04	3.27	-0.01	0.04	3.01	-0.05	0.03	2.69	0.22
	Gas* vol.	0.08	3.36	2.22	0.08	3.01	1.85	0.06	2.67	1.90
	CRB* vol.	0.01	3.31	-0.98	0.01	3.06	-1.09	0.01	2.72	-1.15
	Oil vol.	0.03	3.24	0.18	0.03	3.01	0.34	0.03	2.71	0.50
	Gas vol.	0.08	3.36	2.27	0.08	3.00	1.91	0.06	2.65	1.95
	CRB vol.	0.00	3.34	-1.11	0.00	3.07	-0.80	0.01	2.74	-1.29
Number		0.00						0.01		
	TA-100 vol.	0.01	1.55	1.36				0.02	4.79	0.11
	TA-100 spread	0.00	1.42	-1.55				0.00	4.88	-1.00
	USD/ILS vol.	0.01	1.63	-1.92				0.01	5.40	-2.91
	Oil* vol.	0.01	1.40	0.49				0.03	4.71	-1.12
	Gas* vol.	0.01	1.50	2.24				0.04	4.91	1.86
	CRB* vol.	0.01	1.36	-1.72				0.01	4.82	-1.63
	Oil vol.	0.01	1.32	0.53				0.03	4.70	-1.00
	Gas vol.	0.01	1.52	2.28				0.04	4.93	1.89
	CRB vol.	0.01	1.52	-1.81				0.01	5.14	-2.47

Table 2: Forward and expert inflation forecasts predictive ability tests. CPA is the p-value of the conditional predictive ability test. *terror* is the t-test of the terror variable considered. *control* is the t-test of the control variable considered. A positive t-test means that expert forecasts are better than market-based ones. A negative t-test means the opposite. $Total$ is the sum of those killed and wounded, and $Number$ is the quantity of terrorist attacks. Variables with $*$ are in USD.

NII, is the most powerful predictor of forecast accuracy. This result might be related to the great importance forecasters and markets give to frequency compared with severity of terrorist attacks (Pizam and Fleischer, 2002). Since the outcome of an attack in terms of casualties is much more stochastic than its occurrence, it makes perfect sense that people respond to the number of attacks, regardless of whether the terrorists claimed many victims; yet, this seems to be contradicted by the poor performance of the number of attacks, as measured by GTD. This might be driven by the screening methodology of GTD (text mining methodology), which can easily cause minor attacks to be excluded, thereby creating a more noisy measure of the number of attacks, while still being very accurate in terms of victims.

Similarly, the good performance of gas price volatility is hardly surprising, given the role natural gas production has played for Israel in the last few years. Interestingly, this indicates that uncertainty concerning external conditions (oil and commodity prices) is far less important than factors that might actually affect production in Israel directly (e.g., gas prices and terrorism).

Forecast error vs. mismeasurement of expectations Technically, neither of the market-based measures we use is a pure measure of inflation unless we assume risk-neutral investors. Rather, breakeven inflation corresponds to the inflation expectation plus an inflation risk premium. If the effect of terrorism were increasing uncertainty, for example, in terms of the political response, this might easily create inflation risk. If agents were risk averse, this would affect breakeven inflation. Even if the accuracy of market expectations were to remain unchanged, the forecast performance of breakeven inflation rates might thereby deteriorate, as they are no longer an accurate measure of expectations.

In this section, we test whether the relative deterioration of breakeven inflation from the sovereign bond market compared with professional forecasters is driven by this mismeasurement. To this end, we generate a measure of inflation uncertainty that accounts for the potential impact of terrorism. We estimate a recursive window, pseudo out-of-sample generalized autoregressive conditional heteroscedasticity (GARCH) forecast of year-over-year inflation. Both the variance of shocks and the process itself are modeled as an autoregressive moving average model (ARMA)(1,1) process. In addition, we include terrorism as an exogenous determinant of shocks.[26]

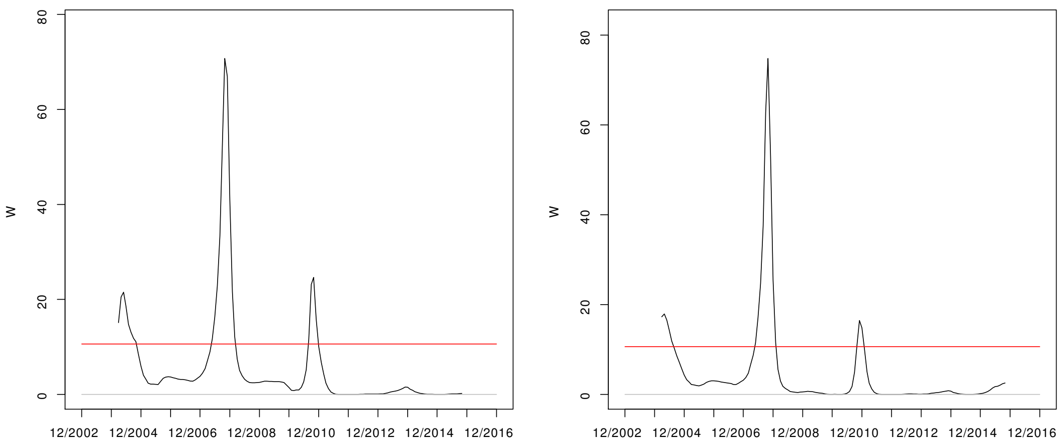
While we find that the standard deviation of expected inflation as mea-

[26] We use the best-performing measure from our study, that is, number of attacks as reported by the NII.

sured by our GARCH has a robust and sizable impact on the relative forecast performance, terrorism remains robust in explaining relative predictive ability. In other words, our results are twofold. (a) It seems that terrorism truly affects the predictive ability of market participants. Even when accounting for risk, we find that terrorism matters. (b) Nevertheless, there is evidence that inflation risk matters. This indicates that market participants are far from risk neutral. This makes using breakeven inflation rates as a substitute for forward-looking measures of inflation in policymaking even more problematic.

4.2 Exchange rate

Unbiasedness Regarding unbiasedness, results for the USD/ILS exchange rate are fairly similar to those for inflation. Fig. 8 shows that our test for unbiasedness in unstable environments strongly rejects both expert forecasts and market-implied exchange rate (USD/ILS) expectations.



(a) Expert forecast

(b) Market-based forecast

Figure 8: Unbiasedness test (USD/ILS). Confidence interval: 5%.

The rejection is again driven by a few isolated periods, particularly by a strong bias between 2007Q2 and 2008Q1 and between 2009Q2 and 2010Q1, as well as before 2004Q4. Substantial terrorism (Second Intifada, 2000Q3–2005Q1) and financial (the subprime crisis,[27] 2007Q2–2008Q4, and Greek

[27] As far as the United States is concerned, Cecchetti (2009) and Mishkin (2010) consider that the crisis began in 2007Q1, when several large subprime mortgage lenders started

crisis,[28] 2009Q4–2010Q3) uncertainty increased during these periods. As Section 4.1 shows, the underlying Wald statistics pick up some movement during the highest violence level of the Second Intifada (2004Q1–Q2).

These rationality tests support the conclusion that terrorism strongly affects expectations and, thereby, expert and market-based forecasts.

Relative forecast performance and encompassing Like inflation, expert and market-based exchange-rate forecasts are affected by uncertainty of a similar order of magnitude. Neither the fluctuation test (Fig. 9) nor the one-time reversal test rejects,[29] even at the beginning of the period (Second Intifada). This confirms that at any point in time, expert and market-based forecast performances are fairly similar (with a confidence interval of 5%).

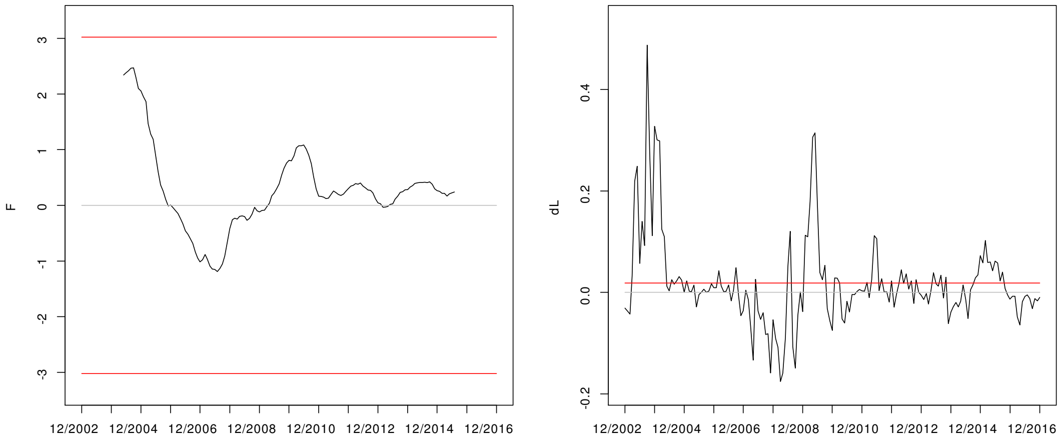
Fig. 9 shows the dynamics of the underlying individual test statistics over time. There is some indication that expert forecasts were superior at the beginning of the sample, yet the test statistics are far below the critical value. Between 2005Q1 and 2008Q4, market-based forecasts were slightly superior to expert forecasts. Contrary to inflation forecasts (Section 4.1), the period in which exchange-rate, market-based forecasts were superior to expert forecasts (2005Q1–2008Q4) corresponds to a relatively calm period. The two transition points between superiority of market-based and expert forecasts occurred in very specific periods. The first period corresponds to strong fears involving the victory of the militant Islamic group Hamas in the elections for the second Palestinian Legislative Council, and the second corresponds to Operation Cast Lead (2008Q4–2009Q1). While the first period heralded increasing fears in and around Israel[30] (switching from the superiority of expert forecasts to superiority of market-based forecasts), the second

to report losses. The real trigger for the crisis was in 2007Q3, when the French bank BNP Paribas temporarily suspended redemptions from three of its fund holdings that had invested in assets backed by the US subprime mortgage debt. As a result, credit spreads began widening, interest rates in Europe shot up overnight, and the European Central Bank immediately responded with the largest short-term liquidity injection in its nine-year history (Benchimol and Fourçans, 2017).

[28] At the end of 2009, the three main rating agencies downgraded Greece's credit rating, and during the first two quarters of 2010, three austerity packages were announced by the Greek government. These decisions, also known as a cause of the European Debt Crisis, strongly impacted the Eurozone, Israel's main trade partner (Benchimol, 2016).

[29] Tests reported in Fig. 9 use squared forecast errors as a loss function. Performance differences are defined as market-based loss less expert (survey)-based loss. Thus, high values of the test statistic indicate worse performance of market-based forecasts and the corresponding superiority of expert forecasts.

[30] The Battle of Gaza resulted in Hamas taking control of the Gaza Strip from Fatah (2007Q2); the Israeli military's launch of Operation Hot Winter (2008Q1); and regular, violent terrorist attacks until Operation Cast Lead (2008Q4–2009Q1).



(a) Fluctuation test

(b) One-time reversal test

Figure 9: Fluctuation and one-time reversal tests (USD/ILS). Confidence interval: 5%.

event promised a period of increasing stability[31] (switching from the superiority of market-based forecasts to superiority of expert forecasts). Operation Pillar of Defense (2012Q4) contributed to the deterioration of expert forecasts relative to market-based forecasts. The encompassing test (Fig. 10) highlights the clear rejection that the typically superior survey forecasts encompass market forecasts. However, these rejections are not driven by the same periods that drive the results of our rationality test. Instead, we reject encompassing fairly consistently over time. This indicates that—for the exchange rate—markets constantly monitor and include factors that are not properly accounted for by professionals. While this does not contradict our hypothesis regarding the importance of terrorism, it does not provide support for it either.

Conditional relative forecast performance Interestingly, although the initial tests provide only weak evidence for fluctuations in relative forecast performance, the tests for conditional forecast performance have different implications.

Generally, the results are not quite as clear as they were for inflation. While some conditional predictive ability tests reject some terrorism indi-

[31] This relatively calm period lasted from 2009Q2 until Operation Returning Echo (2012Q1), carried out to stop cross-border attacks, as mortars and rocket fire started had several quarters before.

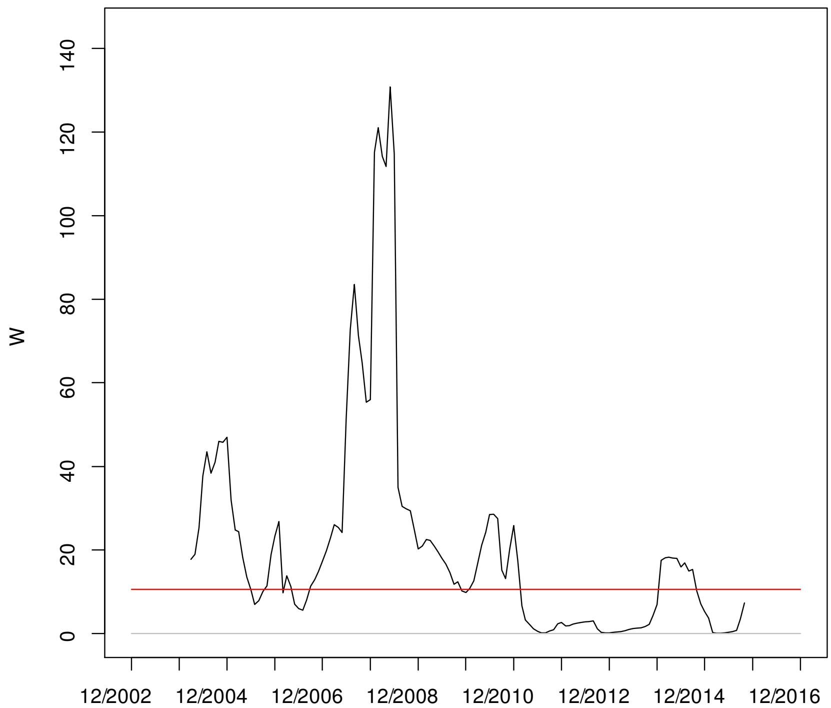


Figure 10: Encompassing test (USD/ILS). Confidence interval: 5%.

cators at the 10% level, we fail to reject them in other cases. The picture changes when accounting for other sources of uncertainty. While the joint test now generally fails to reject the indicators because we add a less powerful indicator, the individual t-tests for the terrorism indicators indicate consistent rejections.

We find again that both terrorism and financial uncertainty explain variations in the exchange rate's (USD/ILS) relative forecast performance. In particular, we find that market forecasts deteriorate more strongly in times of uncertainty compared with expert forecasts. We find evidence that terrorism truly matters for relative forecast performance, and the effect of financial uncertainty becomes insignificant when controlling for terrorism. Neither oil nor gas price fluctuations play a major role.[32]

Given that the variation in forecast performance is well explicable (not random), we believe that it is the lack of power of the fluctuation test in small samples, rather than the constant relative performance, that causes us to fail to reject the null hypothesis.

[32] As a robustness check, we also conduct this exercise with terrorism data excluding Gaza and the West-Bank events (GTD). Our results are similar and available upon request.

Table 3 presents detailed results of the CPA tests when considering the joint test of both market and expert USD/ILS forecasts against control variables[33].

Table 3 indicates that the USD/ILS forecast performance is strongly related to terrorism data. Surprisingly, the NII data now seem clearly less powerful in explaining forecast performance. In particular, the number of attacks, which outperformed all other measures for inflation, is now completely void of predictive power. On the contrary, the number of people killed now plays a major role. The reason might be that—by construction—the exchange market is much more affected by international traders than the Israeli bond market is. Due to the large number of attacks in Israel, terrorism without casualties barely receives international recognition these days. This might explain why the number of casualties (i.e., people killed in attacks) is much more important for the exchange market.

As terrorism has a clear and identified impact on financial and real asset markets (Zussman et al., 2008; Elster et al., 2017), our finding adds to the literature by showing that terrorism has a substantial impact on forward markets involving a significant predictive power loss.

Table 3 shows that the Tel Aviv Stock Exchange (TASE) spread, oil volatility in USD and ILS, and CRB volatility in USD t-tests are generally negative over all our terrorism indicators, indicating that expert forecasts, relative to market forecasts, deteriorate in times of uncertainty (i.e., when the terrorism indicator's t-test is high). These detailed results highlight that forecasters are insignificantly better than 1Y Breakeven market-based inflation forecasts, but forecasters are significantly better than 1Y Forward market-based inflation forecasts.[34]

5 Interpretation

Inflation expert forecasts are superior to market-based forecasts during periods of high uncertainty. The result is qualitatively similar for exchange rate forecasts. In both cases, we find strong evidence that it is indeed terrorism, rather than related phenomena (e.g., commodity price fluctuations and financial distress), that triggers changes in forecast performance. Moreover, we find in both cases that market forecasts deteriorate more strongly.

These results are not surprising. As terrorist attacks affect agents' behavior, market and economic expectations change accordingly. Expert and

[33] A detailed description of control variables representing financial instability (volatility and spreads) is provided in Section 2.3.

[34] This result is mostly driven by the earliest part of our sample (Second Intifada).

		USD/ILS forecasts (1Y)								
		GTD			*MFA*			*NII*		
Terror	Control variable	CPA	terror	control	CPA	terror	control	CPA	terror	control
Killed		0.09			0.11			0.12		
	TA-100 vol.	0.23	4.68	-0.29	0.25	3.46	-0.05	0.25	3.12	-0.04
	TA-100 spread	0.23	4.62	0.44	0.26	3.66	0.80	0.27	3.26	0.67
	USD/ILS vol.	0.21	4.56	1.16	0.22	3.75	1.47	0.22	3.38	1.47
	Oil* vol.	0.23	4.91	-1.87	0.28	3.71	-1.99	0.29	3.34	-1.92
	Gas* vol.	0.25	4.74	0.12	0.30	3.59	0.08	0.31	3.24	0.11
	CRB* vol.	0.24	4.63	0.66	0.27	3.49	0.51	0.28	3.15	0.46
	Oil vol.	0.24	4.78	-1.57	0.28	3.57	-1.39	0.29	3.21	-1.16
	Gas vol.	0.25	4.74	0.08	0.30	3.59	0.05	0.31	3.24	0.09
	CRB vol.	0.23	4.62	0.79	0.24	3.66	0.99	0.25	3.30	0.97
Wounded		0.10			0.17			0.39		
	TA-100 vol.	0.24	4.37	-0.73	0.28	2.06	-0.09	0.16	0.24	0.65
	TA-100 spread	0.25	4.26	0.15	0.35	2.11	-0.27	0.55	0.09	-1.40
	USD/ILS vol.	0.21	4.16	0.97	0.26	2.22	1.20	0.24	0.24	1.09
	Oil* vol.	0.26	4.69	-2.50	0.36	2.26	-2.05	0.25	0.26	-0.84
	Gas* vol.	0.28	4.41	0.17	0.39	2.17	0.15	0.39	0.17	0.76
	CRB* vol.	0.26	4.27	0.08	0.35	2.12	-0.21	0.31	0.22	-0.71
	Oil vol.	0.27	4.48	-1.84	0.37	2.16	-0.97	0.32	0.24	-0.22
	Gas vol.	0.28	4.40	0.14	0.39	2.17	0.12	0.40	0.18	0.70
	CRB vol.	0.24	4.24	0.52	0.30	2.16	0.61	0.29	0.23	0.45
Total		0.10			0.16			0.33		
	TA-100 vol.	0.24	4.50	-0.66	0.28	2.29	-0.10	0.21	0.50	0.62
	TA-100 spread	0.24	4.39	0.23	0.33	2.36	-0.07	0.52	0.37	-1.32
	USD/ILS vol.	0.21	4.30	1.00	0.25	2.48	1.24	0.26	0.52	1.08
	Oil* vol.	0.25	4.80	-2.37	0.35	2.52	-2.10	0.32	0.53	-0.98
	Gas* vol.	0.27	4.54	0.15	0.37	2.42	0.12	0.42	0.45	0.66
	CRB* vol.	0.25	4.40	0.20	0.33	2.35	-0.09	0.35	0.48	-0.56
	Oil vol.	0.26	4.60	-1.82	0.35	2.40	-1.06	0.37	0.51	-0.31
	Gas vol.	0.27	4.54	0.12	0.38	2.42	0.09	0.43	0.45	0.61
	CRB vol.	0.23	4.37	0.58	0.29	2.40	0.67	0.32	0.50	0.47
Number		0.12						0.14		
	TA-100 vol.	0.28	1.11	0.63				0.29	1.45	0.22
	TA-100 spread	0.26	1.08	-1.24				0.33	1.47	-1.17
	USD/ILS vol.	0.27	0.88	0.93				0.28	1.30	0.62
	Oil* vol.	0.27	1.12	-1.16				0.32	1.61	-1.60
	Gas* vol.	0.29	1.08	0.81				0.34	1.45	0.63
	CRB* vol.	0.26	1.03	-0.56				0.33	1.49	-0.67
	Oil vol.	0.29	1.12	-0.59				0.35	1.58	-0.84
	Gas vol.	0.29	1.08	0.76				0.34	1.46	0.58
	CRB vol.	0.29	1.04	0.29				0.33	1.46	0.01

Table 3: Forward and expert USD/ILS forecasts predictive ability tests. CPA is the p-value of the conditional predictive ability test. *terror* is the t-test of the terror variable considered. *control* is the t-test of the control variable considered. A positive t-test means that expert forecasts are better than market-based ones. A negative t-test means the opposite. $Total$ is the sum of those killed and wounded, and $Number$ is the quantity of terrorist attacks. Variables with $*$ are in USD.

market forecasts are then affected in several ways. First, such changes increase forecasting bias and errors. The drastic impact of terrorism seriously affects perceptions of market players and forecasters, which in turn impact their implied forecasts. Second, such events substantially affect the predictive ability of these forecast providers and their updates following the events, at least for the Israeli inflation and exchange rate (USD/ILS) forecasts.

However, the impact on relative performance indicates that there is more to the story: there is an additional fundamental variable that adds some uncertainty. It seems that these events disturb the ability of market participants considerably more than they affect professional forecasters. Again, this is hardly surprising. It makes sense that market participants, in a wider sense, are more affected by the psychological impact of uncertainty than are experimented professionals.

Interestingly, financial uncertainty is not significant when controlling for terrorism, although terrorism remains robustly significant when controlling for financial uncertainty. In other words, terrorism has a major role in both expert and market-based forecasts' bias and predictive ability. Interpreting these forecasts without considering the current terrorism situation could lead to severe mistakes for decision makers.

In line with the recent literature about the impact of oil prices on the US, French, and UK inflation forecasts (Badel and McGillicuddy, 2015; Bec and De Gaye, 2016), for Israel, we show that exchange rate volatility and commodities volatility matter in explaining inflation forecast errors (without considering terrorism data). However, our results suggest that in the case of Israel, terrorism has a strong explanatory power for both expert and market-based error forecasts compared with other control variables (Section 2.3).

Exchange-rate forecasts are significantly impacted by terrorism as well as natural gas price volatility. This link is a consequence of the three ways in which natural gas has influenced the Israeli economy since the 2000s. In the late 1990s, the Israeli government decided to encourage the use of natural gas for several reasons (environmental, cost, and resource diversification). From 2000 to 2016, Israeli natural gas consumption multiplied more than 10-fold (from 0.01 to 0.12 quadrillion BTU). Thus, Israel became an important natural gas consumer. At the same time, several natural gas reserves were discovered in Israel, making Israel one of the 30 natural gas-exporting countries in the world in 2016. Before this, Israel acquired natural gas through Egyptian pipelines in the Sinai Peninsula, which were frequently targeted by terror organizations (e.g., during the August 2012 Sinai attacks). The prominent link between natural gas price volatility and USD/ILS forecasts resides in the Bank of Israel's program to offset the effects of natural gas production on the foreign exchange rate by purchasing foreign currency.

Another layer was added to the Bank of Israel's exchange rate policy in May 2013, following rapid appreciation of the nominal effective exchange rate of ILS (about 11.5% between September 2012 and May 2013). At the beginning of the process, the appreciation was influenced by the geopolitical situation, due to the dissipation of tension prevalent at the beginning of the period. As the start date for natural gas production from the Tamar site drew closer, the foreign exchange market started to price the expected return from dozens of years of natural gas production. The Bank of Israel reacted by launching its natural gas offset program.

These three factors are strongly related to imported inflation and the exchange rate (USD/ILS). As the Bank of Israel tried to offset ILS appreciation due to natural gas production and exports, natural gas price volatility became a robust control variable, considering Israeli inflation as well as USD/ILS exchange-rate forecasts.

As mentioned before, the implied market forecasts are actually a combination of market expectations and risk premia.[35] While we aim to control for that effect, we can only partly do so; that is, we can account for the inflation risk itself (Section 4.1). Other factors that might be affected in times of economic uncertainty such as liquidity risk have to be omitted due to lack of data.[36]

6 Policy implications

The Bank of Israel, as with any other developed country's central bank, uses market-based as well as expert forecasts to implement and justify its own forecasts used for monetary policy decisions.[37] These forecasts are also of prime importance because of their utilization: they are presented and discussed by the MPC and by decision makers and institutions in Israel and abroad (e.g., the International Monetary Fund, Organisation for Economic Co-operation and Development, and the World Bank). From a policy perspective, it is thus of minor importance whether our market forecasts are

[35] Including the liquidity premium reflecting the different liquidity of nominal and inflation-linked government bonds.

[36] Greater war risks narrow the breakevens and affect many other financial asset prices (Rigobon and Sack, 2005). Narrowing of the US breakevens during the global financial crisis represented an investor preference for the liquidity of nominal government bonds (Fleckenstein et al., 2014; Pflueger and Viceira, 2016). The difference between forward exchange-rates and actual physical expectations (foreign exchange risk premium) could also represent compensation for facing disaster risk (Farhi et al., 2009), reinforcing our conclusions for Israel.

[37] See Section 2.2.

truly forecasts in the original sense of the word. What matters is that they are treated as such by policymakers despite their shortcomings.

Our results show that using or interpreting these forecasts (expert and market-based), without considering terrorism in Israel can cause an incorrect perception of their current predictive power. Underestimating forecast errors and correspondingly overestimating predictive ability could lead to severe over-reliance on the wrong forecasts.

Consequently, when establishing their inflation and exchange rate projections, these institutions and decision makers should interpret expert and market-based forecasts differently, conditional on the current level of terrorism. For example, during 2008Q4–2010Q3, these institutions should have considered a persistent and robust bias in expert and market-based forecasts of inflation.[38]

While prior literature and policy discussions have considered economic factors that impact inflation expectations (and thus, the forward-looking estimates of the inflation gap), these factors (e.g., financial instability and commodity prices) have not included terrorism despite their seeming far more important.

The same argument holds true for exchange-rate forecasts. During the last few decades, Israeli monetary policy was strongly influenced by the USD/ILS exchange rate. Although some new challenges have emerged, the exchange rate still has an impact on the monetary policy decision process. Thus, when policymakers evaluate the future path of the Israeli economy and consider the exchange rate (market-based and expert) forecasts, they should also consider the current terrorism situation to avoid biased or low predictive abilities of the forecasts they use.

Risk matters when considering breakeven inflation as a measure of expectations to some degree.[39] That said, terrorism still seems to affect the actual underlying expectation. This result should be considered when the MPC assesses inflation forecasts. When policymakers evaluate the future path of the

[38]Flexible inflation targeters, such as the Bank of Israel, represent their monetary policy objectives in terms of the path of the inflation gap they are willing to tolerate following a cost-push shock until the economy moves back to the inflation target. In practice, central banks formulate the normative trade-off between inflation and output variability in this natural and intuitive way, thus improving communication with the general public (Cukierman, 2015). This inflation gap makes use of inflation (market-based and expert) forecasts to make a decision today on the monetary policy rate to be implemented tomorrow. Therefore, underestimating forecast error and predictive ability performance during periods of terrorism could result in errors/bias in critical monetary policy decisions.

[39]Our finding that terrorism impacts market-based inflation forecasts remains robust when controlling for inflation risk. Nonetheless, we find a substantial impact of risk measures on breakeven inflation.

Israeli inflation and exchange rates, they should give higher weight to expert forecasts during periods of terrorism. However, the encompassing tests suggest that market-based forecasts should not be dismissed entirely but provide some information.

As a conclusion, two practical solutions for the policymaker, concerning decisions using forecasts extracted after terrorist attacks, can be drawn from our findings. The first solution is to extract and analyze the forecasts published before the terrorist attack and to give it stronger weight in the current decision process. The second solution is, in this configuration, to prefer expert-based to market based forecasts.

7 Conclusion

As a small, developed, open economy implementing an inflation-targeting monetary policy under the situation of financial and terrorism instability, Israel remains the best laboratory for analyzing inflation and exchange-rate forecasts.

The consequences of terrorist attacks on expert as well as market-based forecasts are absent from the literature.

This study fills that gap by showing that inflation and exchange-rate forecast errors in Israel were significantly impacted by terrorism over the last 15 years. Moreover, under all types of uncertainties analyzed in this study, expert inflation forecasts are generally better than breakeven (market-based) inflation forecasts.

When considering the number of terrorist attacks, the picture is very clear: whatever the type of inflation forecast, the number of terrorist attacks has the best explanatory power for the relative predictive ability of the forecasts we consider. Both components of market-based inflation forecasts are significantly impacted by terrorism (inflation forecast as well as its risk premium), even if agents are not risk neutral.

We also show that oil and TASE-100 control variables are sometimes found to impact inflation forecasts, a result in line with Bec and De Gaye (2016), although this finding depends strongly on the terrorism indicator included in the model.

Exchange-rate forecasts are more strongly impacted by the number of fatalities from terrorist attacks, whatever the quantitative methodology for accounting for them. We relate this to the fact that external market participants in the exchange market give higher weight to attacks in which human lives are lost.

Uncertainty in general and terrorism in particular affects market participants much more than professional forecasters anticipate. At least in the case of Israel, the weak average performance of market participants seems to be mostly driven by those episodes.

Policymakers should pay attention to market-based forecasts and prefer expert forecasts during periods of terrorism. Forecasters' experience and low-frequency of updating could play a role in their superior predictive ability compared with market-based forecasts.

References

Abadie, A., Gardeazabal, J., 2003. The economic costs of conflict: a case study of the Basque Country. American Economic Review 93 (1), 113–132.

Adeney, R., Arsov, I., Evans, R., 2017. Inflation expectations in advanced economies. RBA Bulletin March Quarter, Reserve Bank of Australia.

Badel, A., McGillicuddy, J., 2015. Oil prices and inflation expectations: is there a link ? The Regional Economist Federal Reserve Bank of St. Louis (July).

Bec, F., De Gaye, A., 2016. How do oil price forecast errors impact inflation forecast errors? An empirical analysis from US, French and UK inflation forecasts. Economic Modelling 53 (C), 75–88.

Benchimol, J., 2016. Money and monetary policy in Israel during the last decade. Journal of Policy Modeling 38 (1), 103–124.

Benchimol, J., Fourçans, A., 2017. Money and monetary policy in the Eurozone: an empirical analysis during crises. Macroeconomic Dynamics 21 (3), 677–707.

Blomberg, S. B., Hess, G. D., Orphanides, A., 2004. The macroeconomic consequences of terrorism. Journal of Monetary Economics 51 (5), 1007–1032.

Caraiani, P., 2016. The role of money in DSGE models: a forecasting perspective. Journal of Macroeconomics 47 (B), 315–330.

Caruso, R., Klor, E. F., 2012. Political Economy Studies on the Israeli-Palestinian Conflict: Introduction. Peace Economics, Peace Science and Public Policy 18 (2).

Cecchetti, S., 2009. Crisis and responses: the Federal Reserve in the early stages of the financial crisis. Journal of Economic Perspectives 23 (1), 51–75.

Crain, N. V., Crain, W. M., 2006. Terrorized economies. Public Choice 128 (1-2), 317–349.

Cukierman, A., 2015. The choice of flexibility in targeting inflation during normal times and during disinflations. Research in Economics 69 (4), 494–502.

Diebold, F. X., Mariano, R. S., 1995. Comparing predictive accuracy. Journal of Business & Economic Statistics 13 (3), 253–63.

Dorsett, R., 2013. The effect of the troubles on GDP in Northern Ireland. European Journal of Political Economy 29 (C), 119–133.

Dreher, A., Fischer, J. A., 2010. Government decentralization as a disincentive for transnational terror ? An empirical analysis. International Economic Review 51 (4), 981–1002.

Dreher, A., Fuchs, A., 2011. Does terror increase aid ? Public Choice 149 (3), 337–363.

Dreher, A., Gassebner, M., 2008. Does political proximity to the U.S. cause terror ? Economics Letters 99 (1), 27–29.

Dreher, A., Gassebner, M., Siemers, L.-H., 2010. Does terrorism threaten human rights ? Evidence from panel data. Journal of Law and Economics 53 (1), 65–93.

Eckstein, Z., Tsiddon, D., 2004. Macroeconomic consequences of terror: theory and the case of Israel. Journal of Monetary Economics 51 (5), 971–1002.

El-Shagi, M., 2011. Inflation expectations: Does the market beat econometric forecasts ? The North American Journal of Economics and Finance 22 (3), 298–319.

El-Shagi, M., Giesen, S., Jung, A., 2016. Revisiting the relative forecast performances of Fed staff and private forecasters: A dynamic approach. International Journal of Forecasting 32 (2), 313–323.

Eldor, R., Melnick, R., 2004. Financial markets and terrorism. European Journal of Political Economy 20 (2), 367–386.

Elster, Y., Zussman, A., Zussman, N., 2017. Rockets: the housing market effects of a credible terrorist threat. Journal of Urban Economics 99 (C), 136–147.

Farhi, E., Fraiberger, S. P., Gabaix, X., Ranciere, R., Verdelhan, A., 2009. Crash risk in currency markets. NBER Working Papers 15062, National Bureau of Economic Research, Inc.

Fielding, D., 2003a. Counting the cost of the Intifada: consumption, saving and political instability in Israel. Public Choice 116 (3-4), 297–312.

Fielding, D., 2003b. Modelling political instability and economic performance: Israeli investment during the Intifada. Economica 70 (277), 159–186.

Fleckenstein, M., Longstaff, F. A., Lustig, H., 2014. The TIPS-Treasury bond puzzle. Journal of Finance 69 (5), 2151–2197.

Gerlach, J. R., Yook, Y., 2016. Political conflict and foreign portfolio investment: Evidence from North Korean attacks. Pacific-Basin Finance Journal 39, 178–196.

Giacomini, R., Rossi, B., 2010. Forecast comparisons in unstable environments. Journal of Applied Econometrics 25 (4), 595–620.

Giacomini, R., White, H., 2006. Tests of conditional predictive ability. Econometrica 74 (6), 1545–1578.

Hawkins, D., 1987. A test for a change point in a parametric model based on a maximal Wald-type statistic. Sankhya A: The Indian Journal of Statistics 49 (3), 368–376.

Johnston, R., 2016. Terrorism, counterterrorism, and unconventional warfare. Tech. rep., Johnston's Archive.
URL http://www.johnstonsarchive.net/terrorism/terrisraelsum.html

Keefer, P., Loayza, N., 2008. Overview: terrorism, economic development, and political openness. In: Keefer, P., Loayza, N. (Eds.), Terrorism, economic development, and political openness. Cambridge University Press, pp. 1–14.

Larocque, D., Lincourt, G., Normandin, M., 2010. Macroeconomic effects of terrorist shocks in Israel. Defence and Peace Economics 21 (4), 317–336.

Mincer, J. A., Zarnowitz, V., 1969. The evaluation of economic forecasts. In: Economic forecasts and expectations: analysis of forecasting behavior and performance. NBER Chapters. National Bureau of Economic Research, Inc, pp. 3–46.

Mishkin, F., 2010. Over the cliff: From the Subprime to the Global Financial Crisis. Journal of Economic Perspectives 25 (1), 49–70.

Newey, W. K., West, K. D., 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica 55 (3), 703–708.

Pflueger, C. E., Viceira, L. M., 2016. Return predictability in the treasury market: real rates, inflation, and liquidity. In: Handbook of Fixed-Income Securities. John Wiley & Sons, pp. 191–209.

Pizam, A., Fleischer, A., 2002. Severity versus frequency of acts of terrorism: which has a larger impact on tourism demand ? Journal of Travel Research 40 (3), 337–339.

Rigobon, R., Sack, B., 2005. The effects of war risk on US financial markets. Journal of Banking & Finance 29 (7), 1769–1789.

Roberts, B. W., 2009. The macroeconomic impacts of the 9/11 attack : evidence from real-time forecasting. Peace Economics, Peace Science and Public Policy 15 (2), 1–29.

Romanov, D., Zussman, A., Zussman, N., 2012. Does terrorism demoralize? Evidence from Israel. Economica 79 (313), 183–198.

Rossi, B., Sekhposyan, T., 2016. Forecast rationality tests in the presence of instabilities, with applications to Federal Reserve and survey forecasts. Journal of Applied Econometrics 31 (3), 507–532.

Ruiz Estrada, M. A., Koutronas, E., 2016. Terrorist attack assessment: Paris November 2015 and Brussels March 2016. Journal of Policy Modeling 38 (3), 553–571.

Sandler, T., Enders, W., 2008. Economic consequences of terrorism in developed and developing countries: an overview. In: Keefer, P., Loayza, N. (Eds.), Terrorism, economic development, and political openness. Cambridge University Press, pp. 17–47.

Shoham, A., Rosenboim, M., Malul, M., Saadon, Y., 2011. Core and periphery - the dual effect of terror. Peace Economics, Peace Science, and Public Policy 17 (1), 1–15.

West, K. D., McCracken, M. W., 1998. Regression-based tests of predictive ability. International Economic Review 39 (4), 817–840.

Zussman, A., Zussman, N., Nielsen, M. O., 2008. Asset market perspectives on the Israeli-Palestinian conflict. Economica 75 (297), 84–115.