# Forecast Performance in Times of Terrorism*

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**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, a factor that should be considered by decision-makers. We focus on terrorism as a mostly endogenously driven form of political uncertainty and assess the forecasting performance of market-based 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, the performance of both market-based and expert forecasts is significantly worse during such periods. Thus, policy-makers should be particularly attentive to terrorism when considering inflation and exchange rate forecasts.

*Keywords:* Inflation, Exchange rate, Forecast performance, Terrorism, Market forecast, Expert forecast.

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# 1 Introduction

In recent years, more and more 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 safe.[1]

Although this has led to greater understanding of the real economic impact of terrorism, little attention has been paid to the impact of terrorism on expectations. Given that terrorism by its very definition aims to "intimidate or create panic", omission of the more direct psychological impact that can be seen in the expectations seems problematic.[2] Expectations play a pivotal role in the mechanism of modern macroeconomic models. Central banks, other policy makers, and other public and private institutions rely heavily on professional forecasts and market-implied expectations in their decision-making. Understanding how a climate of fear generated by terrorism affects those expectations and forecasts is useful for proper policy making.

This study aims to fill this gap by using data on Israel, the developed country that has been by far the greatest target of terrorist activity (per capita). 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) terrorist attacks, such as the Second Intifada, Israel's per capita GDP would be higher than its actual GDP. For example, home prices in Israel are lower in regions that are

[1]See, for example, Blomberg et al. (2004), Crain and Crain (2006), Dorsett (2013), Gerlach and Yook (2016), and Ruiz Estrada and Koutronas (2016) among others.

[2]For instance, Wallace and Wild (2010) defines terrorism as "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."

[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 during the London subway bombings, and France at Paris and Nice).

[4]Although our paper focuses on Israel, there are some general implications. It has been argued that the impact of terrorism in the West is different than it is in Israel because of the profound difference in the nature of terrorism in these countries. As terrorism is more frequent in Israel, it can be anticipated and modeled, while terrorist attacks remain profoundly unpredictable (black swan) in other Western countries. However, in recent years this is no longer true, as the Global Terrorism Index readings of France, the United States, and the United Kingdom (Institute for Economics and Peace) have become very close to that of Israel. Moreover, fatalities caused by a single terrorist attack have been higher in European countries than in Israel over the last decade. Therefore, we explicitly distinguish between the frequency and magnitude of terrorist attacks. Other differences also, 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. As such, 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.

more prone to terrorist attacks (Elster et al., 2017). Fielding (2003a) demonstrates that the First Intifada—which he interprets as a measure of political uncertainty—contributed substantially to Israel's low rate of investment, and Fielding (2003b) shows a decline in the amount of investment.

Other contributions highlight the impact of terrorism on GDP and tourism (Ruiz Estrada and Koutronas, 2016), inflation (Shahbaz, 2013) and the exchange rate (Gerlach and Yook, 2016). Local firms' behavior changes with respect to the local environment, leading to changes, for instance, in the inflation of nondurable goods prices in order to sell perishable stocks. Change in inflation is associated with foreign investment reallocation leading to changes in the exchange rate.

In our paper, we focus on the impact on inflation and exchange rate forecasts using both expert and market expectations (implied by the price of inflation-indexed bonds and the forward exchange rate) in Israel. We restrict ourselves to these indicators due to a data availability constraint, since these are the only indicators for which both market-implied and expert forecasts are available at a monthly frequency over a sufficiently long period to provide meaningful estimates.[5]

Before conducting a predictive ability analysis, we will lay the foundation by performing a dynamic analysis of 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. While neither of these tests allow for a formal assessment of our key hypothesis that terrorism affects forecast performance, they are extremely helpful because (a) they allow a visual inspection of forecast performance embedded into a structured framework, and (b) they allow a broader look at performance that accounts for both relative errors and encompassing. This will allow us to show the relation between terrorism and forecast performance on a more intuitive level.

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. 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 the best of our knowledge, this study is the first to conduct a broad analysis

[5] Which is not the case of other economic variables such as consumption or investment.

of how terrorism affects forecast performance and, particularly, the first to compare several types of forecasts through different terrorism measures reflecting the media coverage, nationality and geographic dimensions of the attacks. We find that terrorism affects market participants much more than professional forecasters. At least in the case of Israel, the low average performance of market participants seems to be driven mostly by terrorism. In addition, we find that terrorist attacks affect forecasting performance controlling for the risk premium.

Recent studies about macroeconomic uncertainty, including Farhi and Gabaix (2016) and Scotti (2016) do not deal with terrorism or short-term warfare. Our paper is novel in this respect. Although our key research question is in regard to 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 most of the literature, we do so while fully accounting for the dynamics of forecast performance, linking us to the literature on forecast performance in unstable environments. Most notably this literature includes the papers by Giacomini and White (2006), Giacomini and Rossi (2010), and Rossi and Sekhposyan (2016), whose methods we borrow. However, the literature has grown far beyond those original papers, including an abundance of applications such as Barnett et al. (2014) and El-Shagi et al. (2016), to name just a few.

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 the 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 agents' psychology and expectations, it seems that the literature and institutions making regular use of forecasts 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 a relevant 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.

Our analysis spans from 2000 to 2017, using CPI inflation data at a monthly frequency and terrorism and exchange rate data at a daily frequency. The sources and detailed transformations are presented below.

## 2.1 Terrorism and uncertainty

Major terrorist attacks (Keefer and Loayza, 2008; Roberts, 2009), or frequent small and medium-sized terrorist attacks (Sandler and Enders, 2008; Benchimol, 2016), could affect the economy. The negative impact of terrorism on short-term activity is a result of 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 terrorist incidents affect the bias and predictive abilities of experts as well as market-based forecasts.[6]

In the aftermath of the September 11 attacks and with the rise of terrorist 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 September 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 in 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 in regard to the consequences of terrorism, expectations—including forecasts—were strongly affected.

The emergence of a small, developed market economy in parallel with a wave of terrorist attacks provides an interesting economic example (Eldor and Melnick, 2004; Caruso and Klor, 2012). Israel is a perfect 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, there have been five episodes of intense violence involving Israel: the Second Intifada (September 2000 to February 2005), the Second Lebanon War (July–August 2006), Operation Cast Lead (December 2008 to January 2009), Operation Pillar of Defense (November 2012), and Operation Protective Edge (July–August 2014).

Unlike most terrorist attacks occurring in Europe or the United States, terrorist

[6] We conducted different event studies without robust results. Daily variance 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.

attacks in Israel (Fig. 1) have not involved substantial destruction of property or infrastructure, except during the First and Second Intifada, but they have sometimes led to substantial casualties (Fig. 2).

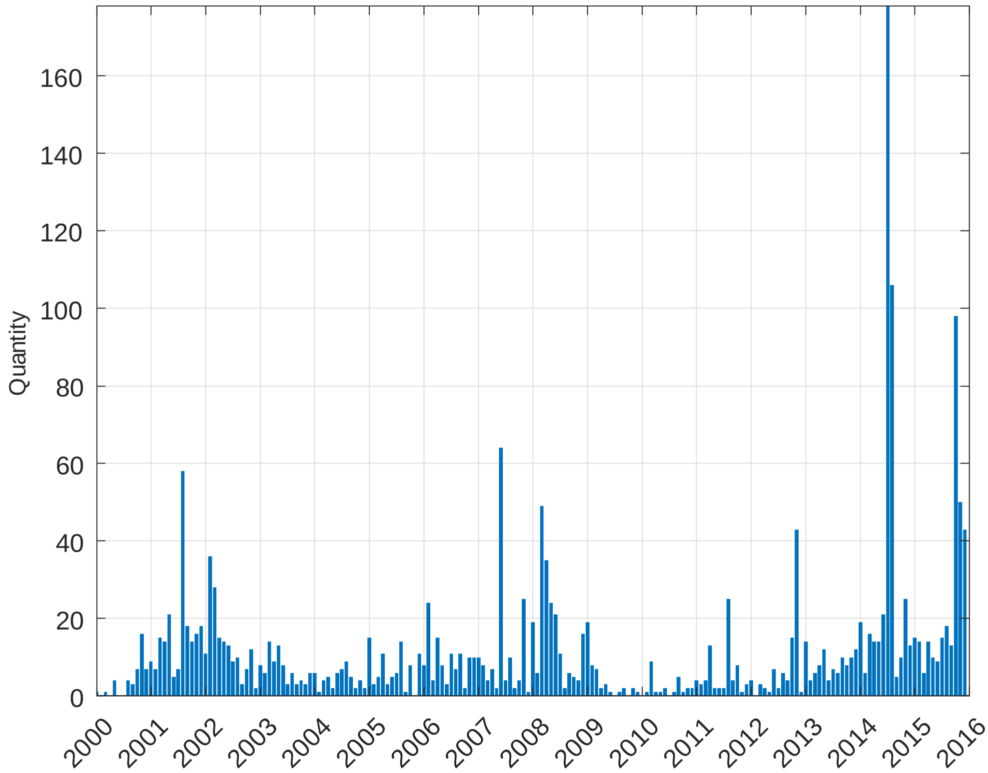



Figure 1: Number of terrorist attacks in Israel between 2000 and 2016. Source: National Consortium for the Study of Terrorism and Responses to Terrorism (START), Global Terrorism Database.

Nevertheless, terrorist attacks affect consumer and investor behavior and, in turn, stock market prices (Shoham et al., 2011; Kollias et al., 2011). When terrorists strike at 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.[7] 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 Data-

[7]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.

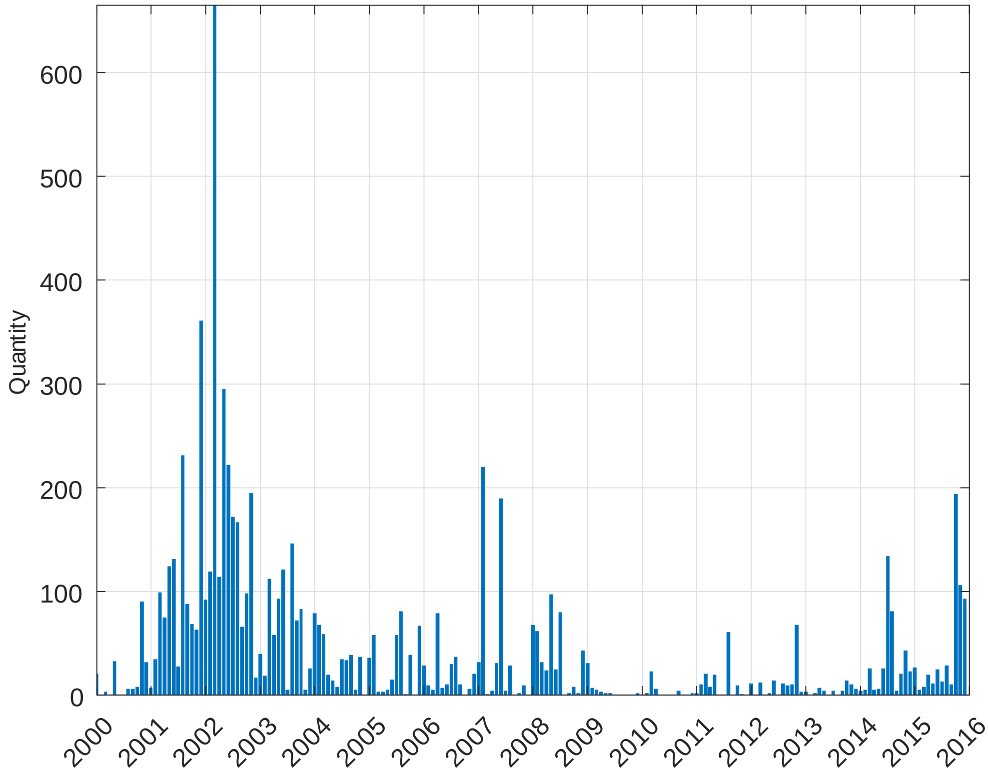



Figure 2: Number of killed and wounded during terrorist attacks in Israel between 2000 and 2016. Source: National Consortium for the Study of Terrorism and Responses to Terrorism (START), Global Terrorism Database.

base,[8] hereinafter GTD) and two government sources (Ministry of Foreign Affairs, MFA; and the National Insurance Institute,[9] NII). The number of terrorist attacks is not available in the MFA data.

These sources have their own methodology to account for terrorist attacks and casualties. For robustness purposes, and to capture the different dimensions and psychological components underlying each terrorism measurement methodology, fear instilled by the media (GTD), fear affecting a specific nationality (NII), or geography (MFA), we use these different data sources.[10]

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 then studies and codes them according to GTD specifications. GTD data are

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

[9] Which provides social security services in Israel, among other things.

[10] Terrorism data are also collected by the Israel Defense Forces and B'tselem. However, those data are not sufficiently recognized in the academic literature, and are potentially less objective than the three databases we consider.

reported separately for pre-1967 Israel, and Gaza and West Bank. To achieve better comparability, in particular with the MFA data, and to account for the fact that most attacks in Gaza and West Bank target Israelis, we aggregate the two datasets. However, tests conducted with only terrorism data on pre-1967 Israel 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 West Bank and Gaza in their definition of Israel.

NII data are from the National Insurance Institute (the State's social security agency). These data include terrorist attacks involving Israelis all over the world, without geographical distinction. That is, in contrast with our other sources (GTD and MFA), this database contains terrorist attacks outside Israel as well.

The most precise database is NII, as the records are double checked–government and social security services–and not based on text mining (GTD) or geography only (MFA). However, we believe GTD has the crucial advantage, due to its reliance on media coverage, of being related more closely to terrorism "perceptions", which is essential for the psychological transmission channel to work.

Although during periods of frequent terrorist attacks, there were months with very few or no terrorist casualties or attacks (e.g., there were roughly 10 people injured in February 2003 and in July 2003, at a time when figures in most months were in the hundreds), we use a backward-looking 12-month moving average for all terrorism indicators because financial data and turmoil are inherently persistent while the effects of terrorism could last a long time (Marsden, 2012; Bandyopadhyay et al., 2014; Karl et al., 2017). The moving average accounts for high volatility by correctly identifying the respective months as part of periods with high instability. Regressions with 3- and 6-month moving averages lead to weaker but qualitatively similar results.

## 2.2 Market and expert forecasts

Israel is one of the rare developed countries with sound economic institutions and developed financial markets (and thus access to very detailed economic information) to have experienced a long history of frequent terrorism. We are particularly interested in market expectations and professional forecasts. Since Israel issues both inflation-indexed and unindexed 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 from different professional sources.[11]

[11] The Bank of Israel publishes an average of forecasts provided by several financial institutions. There are roughly 11 providers of inflation forecasts and 6 providers of exchange rate forecasts (on average, mainly commercial banks) over our sample.

Expert as well as market-based inflation and exchange rate forecasts are useful when formulating the inflation-targeting monetary policy of a small open economy. Thus, the Bank of Israel collects a set of forecasts that are updated regularly.[12]

As per the Bank of Israel's practice, 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 important. However, we do control for inflation risk and exchange rate risk to ensure that our results are not driven by lack of risk adjustment.[13]

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 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.[14] These time series are not transformed and are used as is by the MPC.

In addition, the Bank of Israel collects a series of forecasts provided by professional forecasters, giving an 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 giving us daily data on professional forecasts.[15] The expert forecasts used in our study are computed as the simple arithmetic mean of the inflation forecasts of commercial banks and economic consulting firms. This measure together with the 1Y breakeven inflation forecast are reported in official publications of the Bank of Israel.[16]

The situation is equally good for exchange rates. There is an active ILS/USD future market that allows us to infer market expectations for the exchange rate.

[12]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.

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

[14]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.

[15]Strictly speaking, expert forecasts are not at a daily frequency. The Bank of Israel collects its own expert forecasts based on a system allowing non-costly and private updating ability of their forecasts in an unlimited way. If the forecast is not updated, the previous value is considered. However, because we consider an average of these expert forecasts, and almost all experts update their forecast every week on average over the reviewed period, this time series frequently changes during the month.

[16]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.

Given their importance, exchange rates are covered by the Bank of Israel's in-house survey of expert (banks) forecasters.[17]

In this study, we use the 1Y forward (contract) implied USD/ILS exchange rate forecast as our market-based exchange rate forecast. As practiced in the Bank of Israel the implied exchange rate is not transformed or adjusted in any further way.

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. One year is the only forecast horizon where market and expert forecasts match in Israel.

Detailed descriptions of the performance of the inflation and exchange rate forecasts are provided in Sections 4.1 and 4.2, respectively.

## 2.3 Further control variables

Since we are particularly interested in conditional forecast performance, it is important for us to guarantee that a significant conditionality of forecast performance on terrorism is not due to omitted variable bias. There are other variables that are strongly linked to uncertainty that might be correlated with terrorism. Therefore, our analysis considers a range of control variables explained in the following paragraphs.

Most importantly, market expectations and professional forecasters respond to financial uncertainty.[18] It is well established that asset prices can predict inflation (Stock and Watson, 2003) and foreshadow tail risks in inflation (de Haan and van den End, 2018), and stock, bond and foreign exchange market commove (Pavlova and Rigobon, 2007). Correspondingly, financial market uncertainty can drive inflation uncertainty.

Additionally, our financial control variables allow us, to some extent, to account for the possibility that the impact of terrorism on forecasts is indeed driven by its impact on financial markets. For example, terrorism can affect market liquidity depending on the size of the incident (Chen and Siems, 2004). However, rare large-scale terrorist attacks, combined with improvements in market resilience

[17]The final variable for which implicit market forecasts exist is interest rates, whose expectations can be computed from the yield curve. However, the expert forecasters cover 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.

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

as well as financial stability during the last decade, make liquidity issues less likely to affect our analysis (Peleg et al., 2011).

Financial variables have the additional advantage of usually exhibiting considerable comovement with the business cycle. This is crucial since we cannot explicitly control for business cycle indicators – which are typically measured at quarterly intervals – due to our monthly frequency.[19]

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 the broadest leading index in the Tel Aviv Stock Exchange.[20] 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.

The 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 displays a Pearson correlation of 0.49. The highest level of financial uncertainty was reached during and around the collapse of Lehman Brothers (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 and the (unanticipated) elections for the 18th Knesset[21] 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

[19]Even unemployment, which is traditionally a monthly business cycle indicator, cannot be considered for Israel. Unemployment figures have only been produced at a monthly frequency since 2012, having been produced on a quarterly basis before that.

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

[21]The Knesset is the unicameral national legislature of Israel.

deviation of daily log differences) of crude oil,[22] natural gas,[23] and CRB commodity price index[24] expressed in ILS and USD.

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.

# 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 accounts 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 do well 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 causes an unnecessary loss in power. Thus, the tests are often accompanied 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 Rationality in unstable environments

We start the analysis with the most fundamental question, that is, whether the forecasts we consider are rational. Rossi and Sekhposyan (2016) suggested using the maximum of rolling-window Wald-type rationality tests as the test statistic. Thus, the null hypothesis is that the forecast under consideration is rational at

[22]West Texas Intermediate (WTI) crude oil spot price, US dollars per barrel, not seasonally adjusted. Because of its sulfur concentration, WTI is a better grade of crude oil for the production of gasoline, while Brent oil is more favorable to the production of diesel fuels. Brent's higher sulfur content affected its price as it was more expensive to refine into gasoline. The series of anti-government protests, uprisings, and armed rebellions known as the Arab Spring began spreading across the Middle East in December 2010, and the civil war in Libya escalated in February 2011. These events created concern and worries about the instability in the region, causing volatility in the oil market. The price of the Brent crude rallied relative to WTI crude, the reason being concerns over the availability of supply and logistical considerations, e.g., possible violence on seaway passages. Other world events affected Brent pricing, such as the agreement that Iran would increase the daily amount of Iranian crude flowing into the market. Since Brent is the pricing benchmark for Iranian crude, this pushed the price of Brent down relative to WTI. Last but not least, recent literature uses WTI instead of Brent for Israel (Choi et al., 2018).

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

[24]Thomson Reuters/CoreCommodity Commodity Research Bureau (CRB) index.

every point in time during the sample. Rejection does not imply that a forecast is permanently irrational, but that it was irrational 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 error term of the test regression. The traditional rationality test 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-side variable:

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

where $\theta_0$ and $\theta_1$ are the regression coefficients of the adjusted test equation.[25]

This gives us the more approachable null hypothesis $\theta = \begin{bmatrix} \theta_0 \\ \theta_1 \end{bmatrix} = \mathbf{0}$, which can easily be 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 $\theta$ and $\hat{\Omega}$ is the corresponding heteroscedasticity and autocorrelation consistent (HAC) robust estimator of the covariance matrix of $\hat{\theta}$.[26]

With a sample of $P$ forecasts and using window length $m$, the proposed test statistic takes the following form:[27]

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

where $\mathcal{W}_{j,m}$ is a Wald statistic (as defined in Eq. 3) computed on a subsample using observations $j-m+1$ to $j$.

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

[26]Since it is well established that $\eta_{t,h}$ follows an $MA(h)$ process even for perfectly unbiased 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. We follow the suggestion of Rossi and Sekhposyan (2016) and use a standard Newey and West (1987) estimator for the covariance matrix.

[27]In our study, we use a sample of forecasts of $P = 177$ and 25-month windows ($m = 25$) 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, taking into account the serial correlation.

The distribution of this test statistic depends on whether the uncertainty in the parameter estimates in the forecasting model itself should be accounted for (i.e., not the uncertainty concerning $\theta$ 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 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.

However, using the asymptotic critical values can create fairly sizable distortions in finite samples. For typically available sample sizes (i.e., $P$ between 100 and 200) the number of observations for an individual window quickly becomes extremely small. We therefore use the finite sample adjusted critical values provided by El-Shagi (2019).

## 3.2 Stability of relative forecast performance

### 3.2.1 Fluctuation test

Much like the rationality test in unstable environments is a maximum of individual rationality 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 every 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 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 $\Omega$, which corresponds to $\hat{\sigma}$ 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

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

where $\hat{\sigma}$ is the HAC robust estimator of the standard error of the mean of $\Delta L_{t,h}$.

Since the finite sample bias in the rationality test under instability is mostly introduced by the uncertainty in the estimation of $\Omega$ 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 of the superiority of one forecast over another. For the visual interpretation, we report that $\hat{\sigma}^{-1} m^{-1/2} \sum_{t=j-m+1}^{j} \Delta L_{t,h}$, rather than the corresponding absolute, which is part of the test-statistic, to observe whether the rejection is driven by forecast 1 or forecast 2 to be superior during a subsample.

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

#### 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:

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

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

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

where

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

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 forecast encompassing in the same framework, proposed by Rossi and Sekhposyan (2016), 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

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

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

Contrary to the rationality test, we are merely interested in $\theta_1$. 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 $\theta_1$.

## 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 given by

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

where $T$ is a standard Wald statistic based on pairwise correlations between the elements of $h_t$ and $\Delta L_{t,h}$. $\hat{\Omega}$ is the corresponding HAC robust estimator of the covariance matrix. The test statistic follows a simple $\chi_q^2$ 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 what 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 elements of $h_t$ are simple pairwise 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. The underlying regression is

$$\Delta L_{t,h} = \phi_0 + \phi_1 terror_t + \phi_2 control_t + \eta_{t,h}, \tag{13}$$

where $terror_t$ can be any of our terrorism indicators discussed in Subsection 2.1 and $control_t$ any of the covariates introduced in 2.3.

# 4 Results

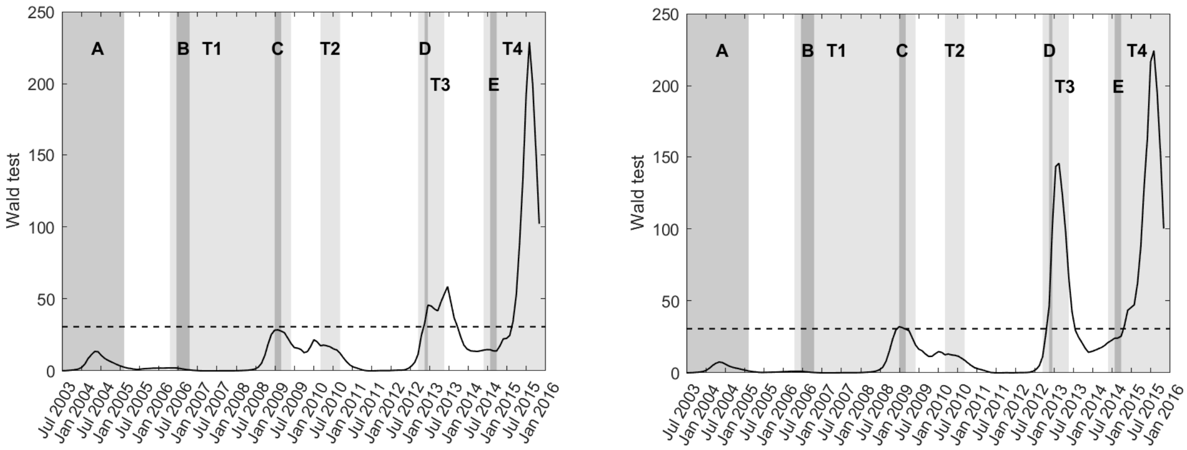
This section presents the results for tests related to the CPI inflation and the USD/ILS exchange rate, as well as expert and market-based forecasts.

Our regressions are monthly mainly because we chose the forecasts that best fit reported inflation in terms of timing, and to avoid useless daily noise from financial variables. This also makes sure that the forecasts can correctly be interpreted and compared as one-year-ahead forecasts.

## 4.1 Inflation

**Rationality** Our rationality test in unstable environments strongly rejects for both expert forecasts and market-implied inflation expectations rationality (Fig. 3).

Since the null hypothesis of the underlying test is that the forecast is always rational, this does not imply irrationality on average or even for a 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 following 2012Q3, which 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, Operation Cast Lead (2008Q4–2009Q1), unanticipated Israeli legislative elections (2009Q1) and financial uncertainty until 2010Q3.



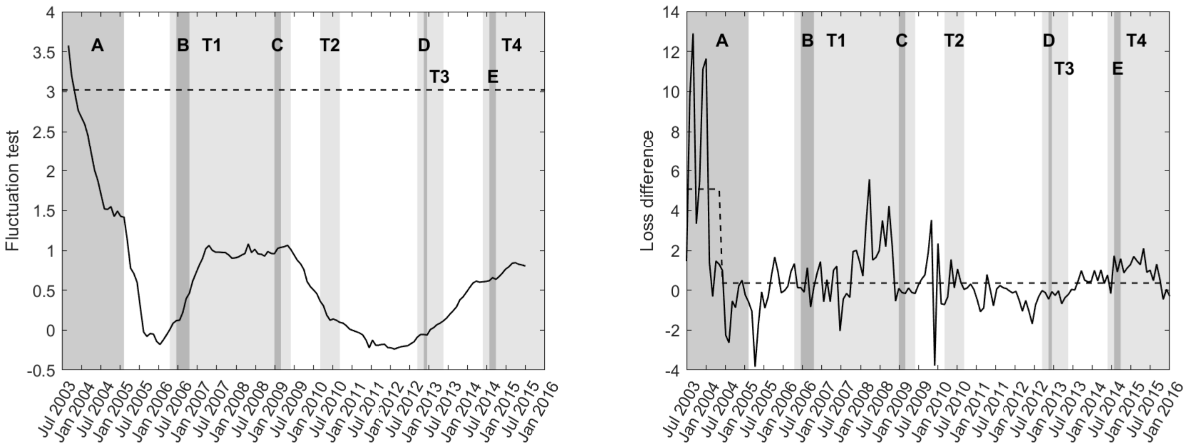

(a) Expert forecast

(b) Market-based forecast

Figure 3: Rationality test statistic (solid) and the critical value (dashed) for CPI inflation. Note: Significance level: 5%. Short warfare (dark gray): Second Intifada (A), Second Lebanon war (B), Operation Cast Lead (C), Operation Pillar of Defense (D), Operation Protective Edge (E). Relatively long terrorism period (light gray): rockets from Gaza and Lebanon (T1), mortars and rockets from Gaza, Flotilla episode and terrorist attacks (T2), terrorist attacks (including abroad), mortar and rockets from Gaza (T3), and Stabbing Intifada mixed with periods of rockets and mortars from Gaza (T4).

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 rejects the null hypothesis of equal forecast performance at each point in time, this rejection is exclusively driven by the early period of the sample, when experts hugely outperformed market expectations. Fig. 4 shows development of the underlying individual test statistics over time, indicating another extended period of superior expert forecasts in the second half of the 2000s. However, the test statistics are far below the critical value. At other times, the performance of both forecasts is almost identical.




(a) Fluctuation test

(b) One-time reversal test

Figure 4: Fluctuation and one-time reversal test statistics (solid), and the critical value and average loss differences (dashed) in (a) and (b), respectively, for CPI inflation. Note: Significance level: 5%. See Fig. 3 for an explanation of the labels.

These 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). 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. 5) paints a clearer picture.

Again, we clearly reject that the typically superior expert forecasts encompass market forecasts. These rejections are mainly driven by the very same periods that drive the results of our rationality test. That is, while both experts and market

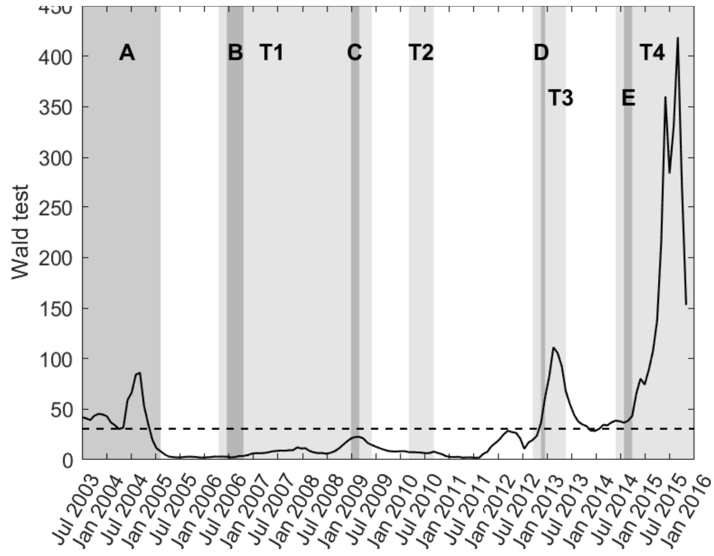



Figure 5: Encompassing test statistic (solid) and the critical value (dashed) for CPI inflation. Note: Significance level: 5%. See Fig. 3 for an explanation of the labels.

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** Our core question is whether terrorist attacks affect the (relative) performance of expert and market-based forecasts. All indicators of terrorism we use turn out to be significant at the 5% level.[28]

To assess the robustness of these 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 with terrorism.[29] First, we include several indicators of financial uncertainty (Section 2.3). Terrorism might cause market turbulence that in turn affects economic forecasts, just as financial turmoil might do when caused by any other source. 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

[28]In addition to the standard model, we run an extended model in which we account for potential nonlinearity by including the square of the terrorism 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 terrorism on forecast performance declines quickly. In other words, it is the existence of terrorism, rather than its degree, that affects forecast performance. However, these results are far from robust and strongly depend on the selection of the terrorism indicator. Therefore, we opt to exclude said nonlinearity from our baseline specification. More detailed results are available upon request.

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

oil producers are located, there might be a relationship between inflation forecasts and commodity price volatility. Commodity prices are known to have a significant influence on the world economy and, specifically, on Israel, which is a small open economy, importing oil, and was a gas importer before developing its 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. In our analysis we focus on significance. To maintain information on the direction of the effect, our tables report t-statistics rather than p-values. Terrorism has a significant effect on relative forecast performance independent of the control variables included in the model. In all cases, the impact of terrorism on the loss difference is positive, implying that the quality of market forecasts deteriorates more strongly in times of high terrorism than that of expert forecasts.

Our modified test relies on regression coefficients rather than correlations for the underlying Wald test statistics, and still finds indicators for terrorism significant 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 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 has an effect on relative forecast performance.[30]

These detailed results highlight that forecasters are insignificantly better than market-based forecasts for 1Y breakeven inflation, but significantly better for 1Y forward inflation.[31]

[30]Other results are available upon request. These tests were conducted with variables expressed in ILS and USD, and considered a 12-month moving average for the control variable. All results confirm that terrorism is the best explanatory variable of inflation forecast errors.

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

| Terrorism | Control variable | GTD CPA | GTD terror | GTD control | MFA CPA | MFA terror | MFA control | NII CPA | NII terror | NII 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 | 1.92 | 2.34 | 0.02 | 3.01 | 2.72 |
| | TA-100 spread | 0.03 | 3.18 | 0.99 | 0.02 | 3.33 | 1.07 | 0.02 | 3.02 | 0.84 |
| | USD/ILS vol. | 0.03 | 2.70 | 0.82 | 0.03 | 2.93 | 0.95 | 0.02 | 2.98 | 0.84 |
| | Oil* vol. | 0.03 | 2.02 | 2.34 | 0.03 | 1.75 | 2.29 | 0.02 | 1.97 | 2.48 |
| | Gas* vol. | 0.04 | 2.66 | 2.09 | 0.03 | 2.57 | 1.82 | 0.02 | 2.50 | 1.89 |
| | CRB* vol. | 0.03 | 3.06 | 1.63 | 0.03 | 3.21 | 1.60 | 0.02 | 3.20 | 1.62 |
| | Oil vol. | 0.03 | 2.35 | 2.11 | 0.03 | 2.32 | 2.14 | 0.02 | 2.38 | 2.26 |
| | Gas vol. | 0.04 | 2.68 | 2.11 | 0.03 | 2.58 | 1.86 | 0.02 | 2.49 | 1.91 |
| | CRB vol. | 0.03 | 2.83 | 1.20 | 0.03 | 2.98 | 1.26 | 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 | | Legend | | 0.05 | 4.10 | 1.73 |
| | Oil vol. | 0.07 | -0.38 | 2.52 | | 1% | | 0.05 | 2.76 | 1.50 |
| | Gas vol. | 0.04 | 0.70 | 2.23 | | 5% | | 0.04 | 3.67 | 1.80 |
| | CRB vol. | 0.08 | 0.40 | 1.12 | | 10% | | 0.05 | 3.51 | 0.96 |

Table 1: Predictive ability tests of 1-year breakeven and expert inflation forecasts.

Note: *CPA* is the p-value of the conditional predictive ability test when only a constant is included. *terror* is the t-test of the terrorism 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.

| Terrorism | Control variable | GTD CPA | GTD terror | GTD control | MFA CPA | MFA terror | MFA control | NII CPA | NII terror | NII 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 | | Legend | | 0.01 | 4.82 | -1.63 |
| | Oil vol. | 0.01 | 1.32 | 0.53 | | 1% | | 0.03 | 4.70 | -1.00 |
| | Gas vol. | 0.01 | 1.52 | 2.28 | | 5% | | 0.04 | 4.93 | 1.89 |
| | CRB vol. | 0.01 | 1.52 | -1.81 | | 10% | | 0.01 | 5.14 | -2.47 |

Table 2: Predictive ability tests of 1-year forward and expert inflation forecasts.
Note: *CPA* is the p-value of the conditional predictive ability test when only a constant is included. *terror* is the t-test of the terrorism 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.

It seems plausible that the number of terrorist attacks as measured by 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 could cause minor attacks to be excluded, thereby creating a distorted 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,[32] 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 this mismeasurement drives the deterioration of the relative forecast performance of breakeven inflation from the sovereign bond market compared with professional forecasters. 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, 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. We also include terrorism as an exogenous determinant of shocks.[33]

Table 3 presents the results of a GARCH(1,1) model. The reported results use the full sample. However, as mentioned above the time series for predicted volatility are based on recursive-window out-of-sample predictions.

[32] See Berrebi and Klor (2008) for an analysis of the causal effects of terrorism on the Israeli electorate's preferences.

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

| | Model with terrorism | | Model without terrorism | |
|---|---|---|---|---|
| | Mean model | | | |
| | Coef. | Std. | Coef. | Std. |
| Const. | 0.859*** | 0.281 | 0.867*** | 0.288 |
| $AR(1)$ | 0.644*** | 0.061 | 0.648*** | 0.061 |
| $MA(1)$ | 0.952*** | 0.013 | 0.952*** | 0.013 |
| | Variance model | | | |
| Const. | 0.012 | 0.015 | 0.021* | 0.011 |
| $AR(1)$ | 0.160** | 0.070 | 0.169** | 0.067 |
| $MA(1)$ | 0.768*** | 0.092 | 0.749*** | 0.090 |
| *terror* | 0.001 | 0.001 | | |

Table 3: GARCH model with and without terrorism. Note: Standard errors are robust. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

The available data on both terrorism and inflation go back much further than our sample of professional forecasts. Therefore, our out-of-sample predictions for the variance of inflation span our entire sample as used for the assessment of forecast performance. In the full sample, we see that the impact of terrorism on inflation variance is minimal at best, indicating that this is not the channel through which terrorism affects forecast performance.

A visual inspection of the time series of predicted standard deviation inflation including and excluding terrorism (Fig. 6) confirms this full sample result for the recursive window estimation. Most of the time, there is no meaningful difference between the predictions generated by the two alternative models.

While we find that the standard deviation of expected inflation as measured 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. It seems that terrorism truly affects the predictive ability of market participants. Even when accounting for risk, we find that terrorism matters. 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

**Rationality** Regarding rationality, results for the USD/ILS exchange rate are fairly similar to those for inflation. Fig. 7 shows that our rationality test in unstable environments strongly rejects both expert forecasts and market-implied exchange rate (USD/ILS) expectations.

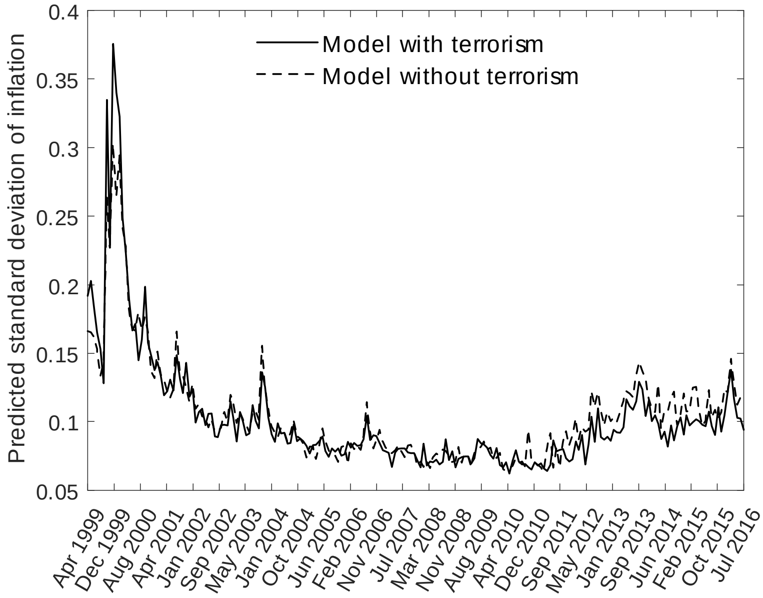



Figure 6: Predicted standard deviation of inflation from the models with and without terrorism.

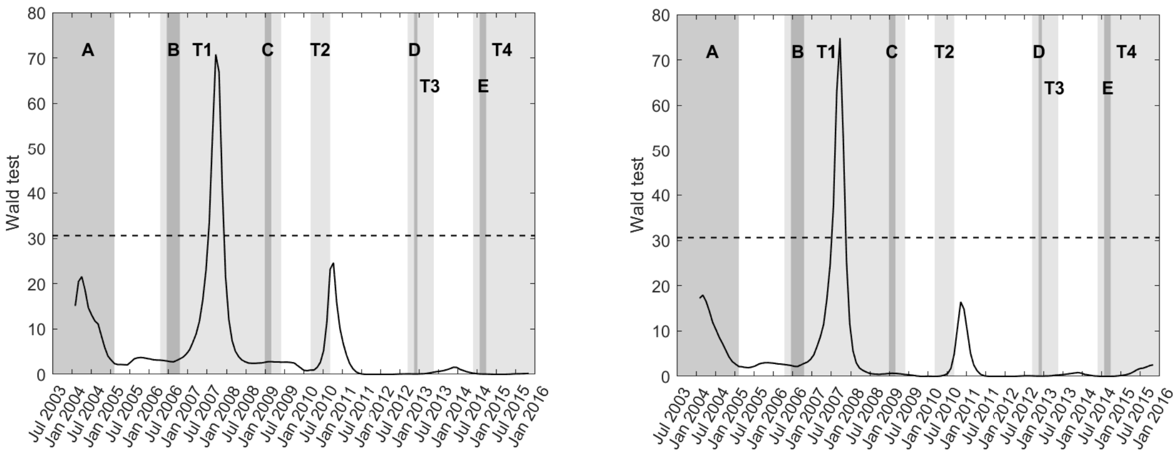
The rejection is driven by a strong irrationality between 2007Q2 and 2008Q1 corresponding to the political and military conflicts between Fatah and Hamas leading to Hamas' takeover of Gaza (Battle of Gaza, 2007Q2–Q3). Substantial terrorism and financial uncertainty (the Subprime crisis,[34] 2007Q2–2008Q4, and Greek crisis,[35] 2009Q4–2010Q3) increased around these periods. As Section 4.1 shows, the underlying Wald statistics pick up some movement during the highest violence level of the Second Intifada.

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. 8) nor the one-time reversal test rejects, 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 (at

[34]In the the United States, Cecchetti (2009) and Mishkin (2010) consider that the crisis began in 2007Q1, when several large subprime mortgage lenders started 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 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).

[35]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 euro area, Israel's main trade partner (Benchimol, 2016).




(a) Expert forecast

(b) Market-based forecast

Figure 7: Rationality test statistic (solid) and the critical value (dashed) for USD/ILS. Note: Significance level: 5%. See Fig. 3 for an explanation of the labels.

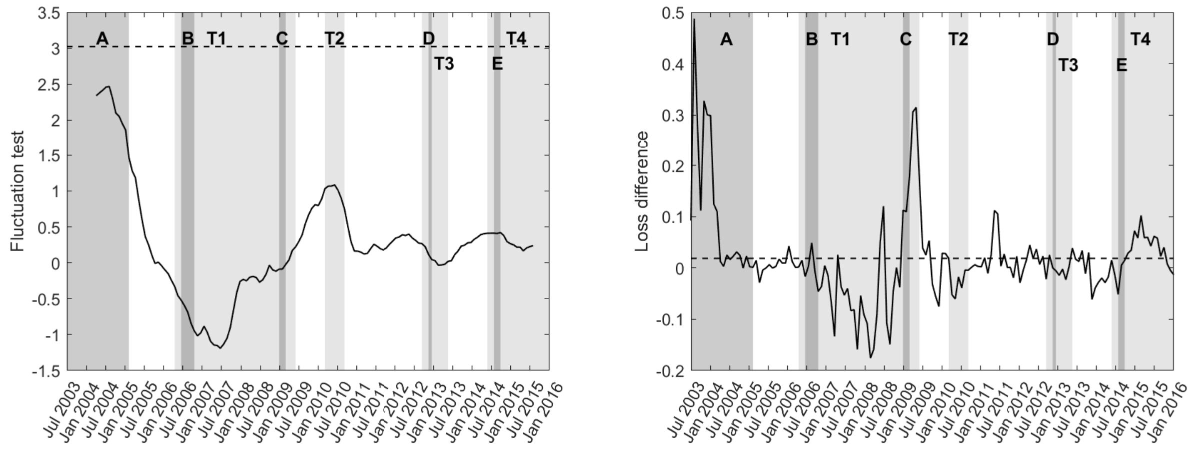
the 5% significance level).

Fig. 8 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. Contrary to inflation forecasts (Section 4.1), market-based forecasts were slightly superior to expert forecasts between 2005Q1 and 2008Q4. This period corresponds to a *relatively* calm period. The two transition points between superiority of market-based and expert forecasts occurred at very specific times. The first corresponds to strong fears involving the Hamas victory 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[36] (and corresponded to the switch from the superiority of expert forecasts to superiority of market-based forecasts), the second event promised a period of increasing stability[37] (and corresponded to the switch from the superiority of market-based forecasts to superiority of expert forecasts). Operation Pillar of Defense (2012Q4) contributed to the performance deterioration of expert forecasts relative to market-based forecasts.

The encompassing test (Fig. 9) highlights the clear rejection that the typically superior expert forecasts encompass market forecasts. However, these rejections

[36]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).

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




(a) Fluctuation test (b) One-time reversal test

Figure 8: Fluctuation and one-time reversal test statistics (solid), and the critical value and average loss differences (dashed) in (a) and (b), respectively, for USD/ILS. Note: Significance level: 5%. See Fig. 3 for an explanation of the labels.

are not driven by the same periods that drive the results of our rationality test. Instead, we reject encompassing fairly consistently until 2008Q2. 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 sufficient support for it either.

**Conditional relative forecast performance** Interestingly, although the initial tests provide only weak evidence of 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 indicators 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.

Table 4 presents detailed results of the CPA tests when considering the joint test of both market and expert USD/ILS forecasts against control variables.

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

| Terrorism | Control variable | *GTD* CPA | *GTD* terror | *GTD* control | *MFA* CPA | *MFA* terror | *MFA* control | *NII* CPA | *NII* terror | *NII* 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 | | Legend | | 0.33 | 1.49 | -0.67 |
| | Oil vol. | 0.29 | 1.12 | -0.59 | | 1% | | 0.35 | 1.58 | -0.84 |
| | Gas vol. | 0.29 | 1.08 | 0.76 | | 5% | | 0.34 | 1.46 | 0.58 |
| | CRB vol. | 0.29 | 1.04 | 0.29 | | 10% | | 0.33 | 1.46 | 0.01 |

Table 4: Predictive ability tests of 1-year forward and expert USD/ILS forecasts.

Note: *CPA* is the p-value of the conditional predictive ability test when only a constant is included. *terror* is the t-test of the terrorism 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.

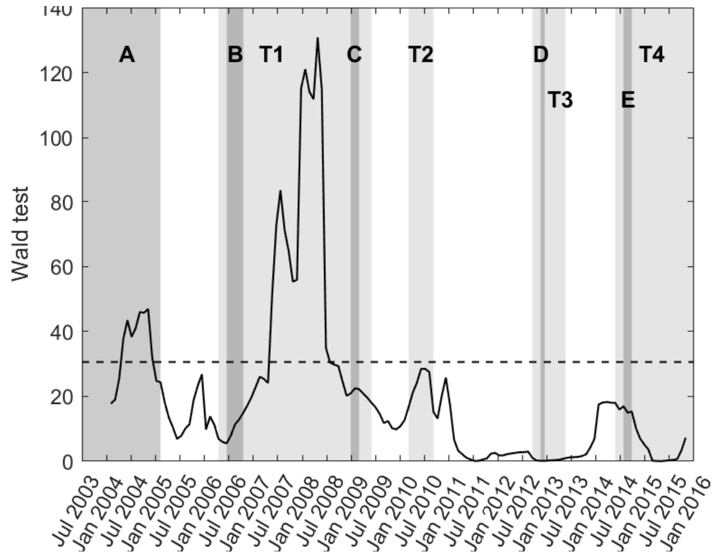



Figure 9: Encompassing test statistic (solid) and the critical value (dashed) for USD/ILS. Note: Significance level: 5%. See Fig. 3 for an explanation of the labels.

relative forecast performance, and the effect of financial uncertainty becomes insignificant when controlling for terrorism. Neither oil nor gas price fluctuations play a stronger role than terrorism.[38]

Given that the variation in forecast performance is quite 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.

Table 4 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 its nature—international traders are much more active in the exchange market than they are in the Israeli bond market. Due to the large number of attacks in Israel, low-casualty terrorism barely receives international mention 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 loss in predictive ability.

Table 4 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

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

our terrorism indicators, indicating that expert forecasts, relative to market forecasts, performance deteriorates in times of uncertainty (i.e., when the terrorism indicator's t-test is high).

# 5 Interpretation

Expert forecasts of inflation 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 the performance of market forecasts deteriorates more strongly.

These results are not surprising. As terrorist attacks affect agents' behavior, market and economic expectations change accordingly. Expert and market forecasts are then affected in several ways. First, such changes increase forecasting bias and errors. The drastic impact of terrorism seriously affects market player and forecaster perceptions, which in turn influence 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–an additional fundamental variable that adds some uncertainty. It seems that these events disturb the predictive 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 experienced professionals.

There are many potential reasons why market forecasts respond differently than professional forecasts. Although a large share of investors (e.g., investment banks) pay attention to the inflation forecasts of professional forecasters, who in turn also keep an eye on the market, the behavior of professional forecasters is singular. Indeed, their objective functions (e.g., in terms of risk aversion) and the time to consider updates of their forecasts lead to significant differences compared to the market-based forecasts. An additional factor–information asymmetry–also contributes to explaining the effect on exchange rate forecasts. Exchange-rate forecasts are supposedly more closely related to international markets, and foreign participants may have different news sources or even preferences.

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 the bias and predictive ability of both expert and market-based forecasts. 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), we show that, for Israel, 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 forecast errors compared with other control variables (Section 2.3).

Both terrorism and the volatility of natural gas prices have significant effects on the exchange rate forecasts. 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 terrorist 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 in the expected return from decades 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 the appreciation of the Shekel 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.[39] While we aim to control for that effect,

[39] Including the liquidity premium reflecting the different liquidity of nominal and inflation-

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.[40]

# 6 Policy implications

Like the central banks of other developed economies, the Bank of Israel uses market-based as well as expert forecasts to back its own forecasts used for monetary policy decisions. 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 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 incorrect 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, between 2008Q4–2010Q3, these institutions should have considered a persistent and robust bias in expert and market-based forecasts of inflation.[41]

While prior literature and policy discussions have considered economic factors that influence inflation expectations (and thus, the forward-looking estimates of the inflation gap), such as financial instability and commodity prices, these factors have not included terrorism despite its apparently far greater importance.

linked government bonds.

[40] 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.

[41] Flexible inflation targeters, such as the Bank of Israel, present 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 market-based and expert inflation forecasts to make a decision today on the monetary policy rate to be implemented tomorrow. Therefore, underestimating forecast error and overestimating predictive ability performance during periods of terrorism could result in errors/bias in critical monetary policy decisions.

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 market-based and expert exchange rate forecasts, they should also consider the current terrorism situation to avoid bias or low predictive ability in the forecasts they use.

Risk matters to some degree when considering breakeven inflation as a measure of expectations.[42] That said, terrorism still seems to affect the actual underlying expectation. This result should be considered when the MPC assesses inflation forecasts. For instance, during the period September 2005 to August 2006 rockets were launched from Gaza and Lebanon (Period T1). During this time, inflation expectations rose and as a consequence of that policy makers dealt with possible transmission from inflation expectations to actual inflation, calling for a rise in interest rates. During that period interest rates had been risen by 2 percent, while actual inflation remained approximately constant. The lesson from this paper is that the extent of that rise shall be discussed in real time under the light of a possible bias in inflation expectations. Terrorism may have reinforced this bias.

When policymakers evaluate the future path of inflation and the exchange rates in Israel, 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, as they do provide some information. The difference in mean difference of squared errors is 1.86 in times of high terrorism (above median), and 0.31 in times of low terrorism (below median). In short, expert forecasts are better in both regimes. Still, there can be a benefit to including the worse forecast if it is not encompassed. However, this seems to be mostly the case in times of extremely high terrorism as in the early part of our sample. Given that this period is inevitably part of the initial training period of a pseudo out of sample forecasting exercise, we are unable to quantify the benefits using our fairly short sample.

Our findings provide two practical solutions for the policymaker concerning decisions using forecasts extracted after terrorist attacks. The first is to assess the forecasts published just before the terrorist attack, i.e., the forecasts prevailing in a period that was not subject to terrorism, and to give them greater emphasis in the current decision process compared to the forecasts published in times of terrorism. The second is to prefer expert-based rather than market-based forecasts in this configuration.

[42] Our finding that terrorism affects market-based inflation forecasts remains robust when controlling for inflation risk. Nevertheless, we find that risk measures have a substantial impact on breakeven inflation forecasts.

# 7 Conclusion

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

The consequences of terrorist attacks on expert as well as market-based forecast performance are absent from the literature. This study fills that gap by showing that terrorism had a significant impact on inflation and exchange rate forecast errors in Israel over the last 15 years. Moreover, under all types of uncertainties analyzed, 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. Terrorism has a significant impact on both components of market-based inflation forecasts (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 affect 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 affected 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, alters the forecasting performance of market participants much more than professional forecasters' one. 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, i.e., less subject to overreaction, could play a role in their superior predictive ability compared with market-based forecasts.

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