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Striking the Implied Volatility of US Drone Companies

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Abstract

This study analyzes the impact of drone strikes on the implied volatility of US drone companies. We find evidence of an overall increase in the implied volatility the day after the strike. We subset drone strikes according to countries targeted and US president in office, finding a more significant impact for strikes in Afghanistan and Pakistan, and under the Bush or Obama's administration. We find that drone strikes are also associated with next day decreasing stock returns of the drone companies. A possible increasing geopolitical risk concern and resiliency rationale may explain our findings.

Keywords: Drone Strikes, Drone Companies, Implied Volatility, Event Study, Geopolitical Risk.

JEL Classification: F5, G12, G14, G18, G41

1 Introduction

The use of drones – unmanned aerial vehicles – for all kinds of purposes is proliferating and fast developing. The drone industry is evolving way beyond its military origin and recreation use towards business and commercial purposes. The drone economy nowadays represents undeniable market opportunities. PwC has estimated the total market value of drone-powered solutions at over US$127bn across a variety of industries. The commercial segment of the drone market

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has grown to include, to cite but a few, utilities intended for delivering packages, providing internet access in remote areas, precision agriculture tools, supervising in construction and related industries, and important humanitarian missions ferrying medical supplies and vaccines to remote areas. Even though the number of drones sold for commercial use is still in its infant phase, the total projected revenue associated with commercial use is forecasted to grow rapidly.[1] Drone companies' profits and stock prices have been on the rise reflecting this evolution.

While military drones have accounted for the vast majority of worldwide spending on drones, this trend is inverting fast, with military suppliers projected to capture just a fraction of the commercial drone market. The drone economy is projected to grow even faster, exploiting the advances in mobile connectivity (e.g. 5G networks) and in artificial intelligence enabling a broader universe of commercial drone applications. Like the internet revolution, mobile phones and GPSs before them, the drone industry is now playing a pioneering role in driving the fourth industrial revolution. The economic relevance of the drone industry is also connected to; jobs creations (e.g. manufacturing, drone operators), the positive impact on businesses and consumers, industries' savings from cost-effective means of inventory, transportation, distribution, as well as a positive environmental impact (since powered by batteries) compared to traditional means of delivery, thereby helping countries to reduce emissions worldwide.

Their use to date however has been mostly associated with military services and scopes, initially adopted by the US for military surveillance and reconnaissance given the focus on information warfare, and subsequently, especially following 9/11, devoted towards armed missions, namely as armed drones – drones on which weapons are installed – thereby aligning the drone industry with the so called war on terror. The expanding use of armed drones as weapons of war has placed them squarely at the center of military strategy by a growing number of countries given the drones greater scope and range of operation, endurance, and alleged precision. However, this use has also placed them at the center of a broader debate, often fueled by the media, surrounding socioeconomic and geopolitical effects. The humanitarian consequences for civilians associated with drone strikes, in addition to questions regarding the legality of such strikes and ethical issues are all legitimate concerns. Furthermore, such strikes might also carry

[1] A report published back in 2016 by Goldman Sachs highlighted the growth in the use of drones as powerful business tools, predicting that of a projected total spend of $100bn on both military and civilian drones over the period 2016 and 2020, the commercial segment would experience the fastest growth, notably in construction, agriculture, insurance and infrastructure inspection. For more details, see https://www.goldmansachs.com/insights/technology-driving-innovation/drones/. Moreover, the World Economic Forum recently announced at its Technology Governance Summit (April 2021) a forecasted global market for delivery drones worth $4.4 bn by 2025 reflecting the rapidly growing use of drones as tools for delivery.

a burden related to people's fears and financial market sentiment. How are drone strikes affecting the drone economy and, especially, the fast-growing drone companies? In this paper, we study the impact of drone strikes serving military scopes for the US on the volatility and price fluctuations of such drone companies.

We aim to contribute to the literature by studying the possible impact of drone strikes by the US on drone companies stock market volatility, believing this to be, as far as we are aware, the first study of its kind. Furthermore, the study of drone strikes can also be considered parallel to areas such as international conflicts and politics, characterizing increasing geopolitical and war risk, as highlighted by the recent assassination of the Iranian general Qasem Soleimani on the 3rd January 2020. At the same time, it draws closely to anti-terroristic operations, therefore our study contributes not only to stock market volatility literature but also to the literature examining the impact of counter-terrorism policies (e.g. Zussman and Zussman, 2006; Bejan and Parkin, 2015). The perceived success of such attacks led to a substantial increase in the use of drones as a strategic tool of the US Central Intelligence Agency and its military around the globe (see Jaeger and Siddique, 2018).

Despite the increase in drone strikes since the early 2000s, the academic literature studying their impact on the economy and financial market appears to be scarce. On the other hand, extensive studies have examined the influence of political events on stock markets, including issues related to both military and political crises, finding that an increase in war or crisis risk is associated with a decrease in equity prices (e.g. Rigobon and Sack, 2005; Wolfers and Zitzewitz, 2009; Berkman et al., 2011). In the period following the events of 9/11, the literature studying the implications of terrorist activity proliferated, spanning its impact on major economic variables such as consumption and exports (e.g. Eckstein and Tsiddon, 2004), economic growth (e.g. Blomberg et al., 2004), consumptions and investments (e.g. Llussá and Tavares, 2011), largely highlighting the negative impact of terrorism on the stock market (e.g. Abadie and Gardeazabal, 2003; Chen and Siems, 2004; Kollias et al., 2011; Narayan et al., 2018; Papakyriakou et al., 2019). See also Wisniewski (2016) for a detailed survey. Some studies have related terrorism with measures of stock market uncertainty both historical (e.g. Nikkinen et al., 2008; Arin et al., 2008; Essaddam and Karagianis, 2014; Corbet et al., 2018) and also implied measures extracted from options (e.g. Bevilacqua et al., 2020).

In the last two decades drone strikes may well have also contributed towards influencing investors' risk preferences and stock market prices due to their possible effect on increasing geopolitical risk and international conflict concerns. Studies have argued that terror not only affects the level of prices, but also changes stock market volatility, both historical (e.g. Arin et al., 2008) and also implied measures extracted from options (e.g. Bevilacqua et al., 2020). We believe that drone strikes may share features similar to terrorist attacks, wars or conflicts, hence can be considered as catastrophic events leading to investors' transmission of negative feelings and fear, increasing anxiety which in turn may affect investors' risk preferences, usually resulting in stock market declines (e.g. Burch et al., 2016). One of the main channels for the transmission of investors sentiment and fear to the stock market is the options market, thereby leading to an increase in the implied volatility of the underlying assets (e.g. Kaplanski and Levy, 2010; Nikkinen and Vähämaa, 2010; Papakyriakou et al., 2019). More recently, drone strikes have also attracted press attention and coverage with respect to their possible linkage with financial markets, as for instance following a drone strike on the 24th September 2019 on a Saudi Arabian oil facility which saw an increase in geopolitical risk concerns.[2]

Terrorist attacks have not only been linked to the broad stock market indices, but also to more specific industries. For instance, Carter and Simkins (2004) investigate the reaction of airline stock prices to the 9/11 terrorist attack. Chesney et al. (2011) find a direct significant negative impact of terrorist events on industries such as travel and airline. Apergis and Apergis (2016) investigate the impact of the 11/13 Paris terrorist attacks on companies in the defence industry, and more recently, Akyildirim et al. (2020) investigate the effects of airline disasters on aviation stocks. Our study can also be considered in a similar way, namely the direct impact of an event on a specific industry, with the main focus being the impact of drone strikes on drone companies implied volatility and stock prices. We believe that the booming drone industry may be directly affected by such strikes.

We collect data on US drone strikes over the last 15 years that targeted countries such as Pakistan, Afghanistan, Yemen and Somalia, countries that have been the target of most drone strikes carried out by the US military. In addition to analyzing the impact of drone strikes on US drone companies, given the long financial data series available we further subset drone strikes according to the countries targeted and also the US president in office to determine whether any pattern exists. We conduct an event-study based regression approach, where we test whether or not a possible pattern is distinguishable by constructing dummy variables that

[2]See https://www.bloomberg.com/news/articles/2019-09-16/u-s-stock-index-futures-slide-after-oil-jumps-on-drone-attack.

proxy for drone strikes with respect to a specific targeted country as well as the incumbent US president in office at the time of the strike.

Our results show that through our event-study based regression approach, we detect an overall increase in the next day drone companies implied volatility following a drone strike. We further find that drone strikes targeting Afghanistan as well as strikes under the Bush and Obama's administrations appear to show higher significance. Our results can be explained by a geopolitical risk concern hypothesis given that drone strikes appear to increase the next day drone companies implied volatility as well as to reduce their stock prices. Patterns uncovered from our results suggest also a resilience of drone companies rational to drone strikes. Several robustness checks confirm our main findings.

The remainder of this paper is organized as follows. In section 2 we unfold a brief literature overview connected to our study. Section 3 describes the data adopted with respect to both the drone strikes database and the drone companies. Section 4 describes the event-study based regression methodology with section 5 reporting the empirical findings with respect to several dummies adopted, dependent variables and regressions specification. Section 6 reports some robustness checks, while section 7 concludes our paper. Additional results are reported in the Appendix of the paper.

2 Related Literature

Prior to a very concentrated focus within the literature on the links between terrorism and financial markets and the economy, several studies explored its effects within a wider capacity on countries and their politico-socio systems (see Enders et al., 1990; Ginges, 1997). The political system of a country can, amongst other things, be a strong indicator of the effects of terrorism on its society and markets, as shown by Karolyi and Martell (2010). Private consumption and private investment have been shown to be significantly and negatively affected by all terror indicators and the largest impact is respectively associated with the number of victims or number of attacks (see Llussá and Tavares, 2011). Dreher et al. (2011) show how the geopolitical impacts of terrorism have unfolded over the years through analyzing the influence of terrorism on migration across 152 countries over a 25 year period, revealing robust evidence that terrorism is among the "push factors" of skilled migration, though is not robustly associated with average migration. Moreover, flourishing businesses become favorable terrorist targets as governments tighten security and increase spending on protection (see Enders and Sandler, 2000). Globalization of our societies has also allowed spillover effects of terrorist attacks from one economy to the next, what with greater developed communication technologies and flow of finances and trade across borders. Kumar and Liu (2013) demonstrate, through a study on the top 63 GDP ranked countries, that when one country is the victim of terrorism notable negative effects are also experienced by trading partners, whereas non-trading partners appear to be left untouched.

One of the first studies on the effects of terrorism on financial markets is undertaken by Abadie and Gardeazabal (2003), studying the impacts of the Basque Fatherland and Freedom (ETA) on stock prices in the Basque Country. They showed that in times of active conflict, Basque firms performed significantly below that of other Spanish regions and vice versa. By the mid 2000s, an increasing number of researchers focused on the impacts of terrorist attacks on the economy and financial markets, a focus most likely attributed to the monumental terror event which shook the world, notably, 9/11. Eckstein and Tsiddon (2004) provide evidence showing the negative effects of terrorist acts on some major economic variables. A subsequent study by Drakos (2010) later back this up, bringing to light the fact that price fluctuations can be attributed to heightened investor conservatism where uncertainty is present. This notion is supported by numerous studies, showing that not only are acts of terror a primary cause of fear among investors, but that one of the main channels of negative feelings transferred in stock markets is investor sentiment (e.g. Burch et al., 2016; Papakyriakou et al., 2019). Having said that, the sensitivity of individual country's markets to terrorism can vary greatly, for instance developing countries require much more time to bounce back from such events (e.g. Mnasri and Nechi, 2016).

It goes without saying that terrorism also plays a major role not only in price levels but also the level of price fluctuations in markets. Conversely however, with regards to financial market volatility, the picture appears to be more blurred. Gulley and Sultan (2009) on examining a number of developed countries discover that market volatility is impacted in some countries, including Canada and Japan, but overall markets are robust and recover quickly from events of extreme fatality such as 9/11. However, a number of studies have countered this finding of resilience. Nikkinen et al. (2008) examine the post 9/11 response of 53 stock markets finding that they each exhibited dramatic increased volatility. Arin et al. (2008), through a multi-country time-series analysis of terrorism on stocks returns and volatility, find that terror attacks significantly impact both, the magnitude of which being greater in emerging markets. Essaddam and Karagianis (2014) study the stocks of American firms, showing abnormal trends on terror event days, trends which were sustained for around fifteen days subsequently. Employing a multivariate GARCH model, Corbet et al. (2018) study the impact of domestic and international terrorist attacks on the volatility of domestic European stock markets, indicating that acts of terrorism that take place within the targeted country significantly influence domestic stock market volatility. A recent study by Bevilacqua et al. (2020) on the effects of terrorism on implied volatility on the U.S. market find through an event study approach, that terror acts within the U.S. impact its markets to a greater extent than events taking place abroad. They also demonstrated greater evidence of impact on puts channel of the VIX as opposed to calls.

At the start of this century, an increase in terrorist attacks forced governments to shift their focus to increased protection and fighting against terror, so called counter-terrorism policies. Rigobon and Sack (2005) measure the effects of the risks associated with the war in Iraq (seen as the central front in the war on terror) on various US financial variables and found that increases in war risk caused a decline in equity prices, uncovering an important "war risk" factor that accounted for a considerable portion of the variances of these financial variables. Wolfers and Zitzewitz (2009) study the financial market participants' expectations of the consequences of the 2003 Iraq war through an ex-ante analysis and showed that a 10% increase in the probability of war was accompanied by a 1.5% decline in the S&P 500. Despite such investor fears and consequences on financial markets, the war on terror only increased in intensity and sophistication over time. Zussman and Zussman (2006) evaluate changes in stock prices surrounding counter-terrorism operations through examining the impact of the Israeli assassination attempts on Palestinian leaders of organizations such as Hamas, Fatah and Islamic Jihad. They found that assassinations of senior Palestinian political leaders leads to a decline in stock market valuations, whereas assassination attempts on senior military leaders causes both the Israeli and the Palestinian stock indices to increase. The first type of assassinations is viewed as counterproductive in combating terrorism, while the second type more of an effective measure, uncovering some insight into the effectiveness of such counter-terrorism policies. A further study by Afik et al. (2016), again within the context of Israel, examine the impact of counter-terrorism acts on stock market returns, finding a positive impact in stock market behavior, believing that this may be the result of the effect of the counter-terrorism operations on the collective mood of investors. Jaeger and Siddique (2018) examine the efficacy of US drone strikes to combat the

Taliban and Al-Qaeda and whether the number and incidence of subsequent terrorist attacks increase or decrease. They find that there are stronger effects of drone strikes on subsequent Taliban and Al-Qaeda attacks in Pakistan than there are in Afghanistan.[3]

The use of drones as a weapon on the so called war on terror has increased over the years. Some have argued that their use to tackle the war on terror has enabled governments to justify state control via technological transcendence (see Salter, 2014). Concerns have also been raised regarding the legality of the use of drone strikes for targeted assassinations given that they actually defy much U.S. and international law, and hold little accountability. The use of drones for military purposes has caused an increase in geopolitical unrest. Despite the increasing use of drone strikes, studies analyzing the effects of such strikes on financial markets and specific industries are scarce. Of the limited studies that have directly examined the impact of such strikes, a study by Naveed et al. (2017) investigated the effects on the Pakistani equity market of U.S. drone strikes as counter-terrorism operations on terrorist targets in Pakistan. They showed that despite an initial negative market response to the drone strike, the response revived in accordance with the characteristics and expected ramifications of the strike, finding overall a positive statistical significance on equity market reactions to major successful drone strikes. This seems to indicate that the use of drones as a counter-terrorism tools is efficacious, though it is important to understand that not all counter-terrorist policies are effective and politics per se has a large role to play in this.

Subsequent literature reviewed revealed no further studies within the context of drone strikes and their impact on stock market returns and volatility and also on the specific US drone industry. Thus, this study attempts to fill the current gap in the existing literature exploring a novel avenue within the relationship between financial markets, counter-terrorism operations and geopolitical risk through the lens of US drone strikes. We also contribute to the broader literature on the impact of exogenous events on financial markets and investors' expectations. Markets and agents react to exogenous shocks which, in addition to terrorist attacks and wars, can include events such as natural disasters (e.g. Lamb, 1995; Shelor et al., 1992; Bourdeau-Brien and Kryzanowski, 2017), social unrest and political upheaval (political risk) (e.g. Erb et al., 1996; Lehkonen and Heimonen, 2015) and also health crises or pandemics (e.g. Papadamou et al., 2020).[4]

[3]On important studies about more specific dynamics of violence between the Israeli military and Palestinian groups, see the papers by Jaeger and Paserman (2006) and Jaeger and Paserman (2008).

[4]See also Barro (2009) and Nakamura et al. (2013) for a thorough discussion on the more general topic of

3 Data

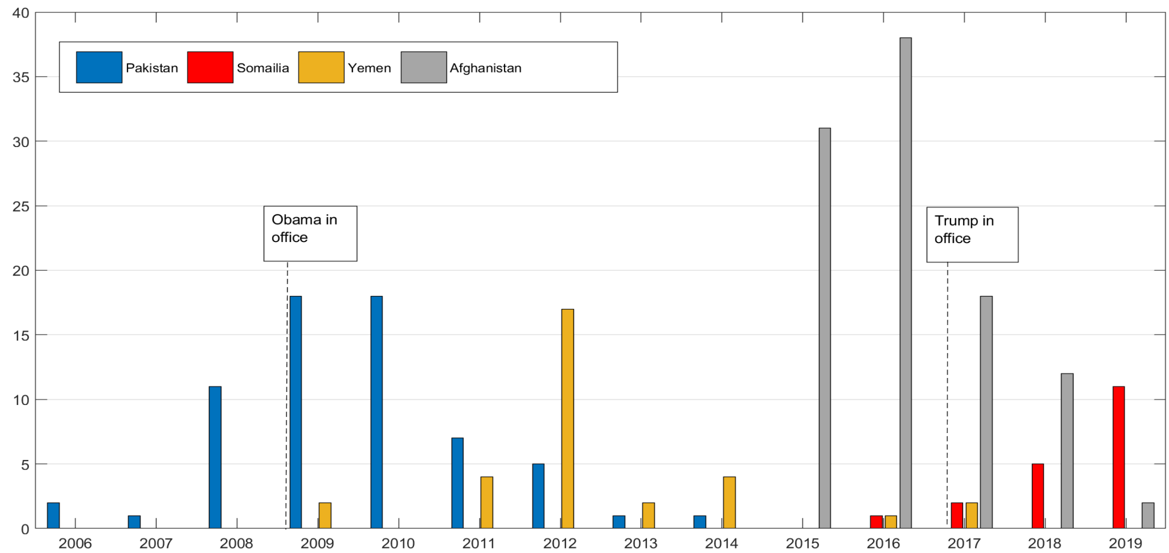
This section outlines the events selection process and sources 3.1, as well as the financial market data used and the implied volatility 3.2.

3.1 Drone Strikes Data

Data on drone strikes is collected from the Bureau of Investigative Journalism from 01-2006 to 12-2019. The Bureau collects data on US strikes in Afghanistan, Pakistan, Somalia and Yemen from government, military and intelligence officials, and from credible media, academic and other sources.[5]

We construct a dummy variable marked 1 for every day with a drone strike in any of these countries with at least 10 fatalities, and 0 otherwise, disentangling this dummy according to the target country, or US president in office. As an example, a dummy variable for Pakistan marks 1 for every day a drone strike hits Pakistan, regardless the US president in office, and 0 otherwise. A dummy variable for Obama marks 1 for every day with a strike under president Obama in any of the four countries, and 0 otherwise. Figure 1 shows the annual number of strikes with at least 10 fatalities over our sample.

Figure 1: **Drone Strikes across Countries**



Notes: This figure shows annual number of drone strikes featuring at least 10 fatalities in the selected countries from 2006 to 2019.

disaster risk.

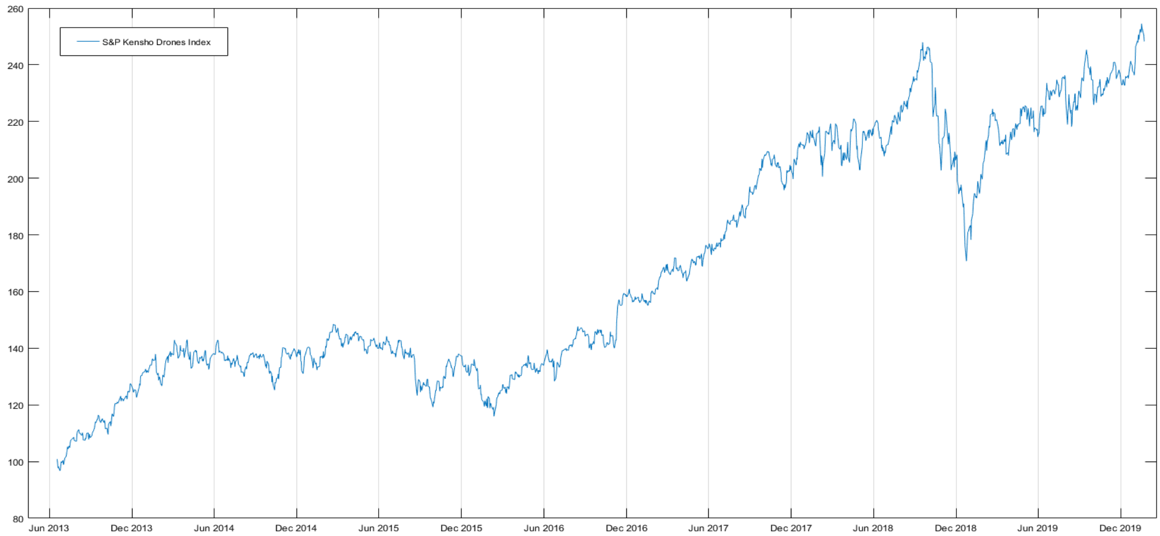
[5]For data and further details, see: https://www.thebureauinvestigates.com/stories/2017-01-01/drone-wars-the-full-data.

We observe that Pakistan has been target of drone strikes mainly from 2006, Afghanistan mainly from 2015, Yemen from 2011, and Somalia in most recent years with more sporadic attacks. With respect to the pattern of strikes according to the US president in office, the Bush administration was associated mainly with strikes in Pakistan, Obama with strikes in Pakistan, Yemen and Afghanistan, while the Trump presidency has been characterized by strikes in Afghanistan, with declining number of strikes in the other countries.

3.2 The Drone Companies

Our analysis focuses on the S&P Kensho Drones Index, an index designed to capture the performance of companies focused on drone-related activities as a principal component of their business strategy.[6] The growth of the index in recent years is evident to see from Figure 2.

Figure 2: **S&P Kensho Drones Index**



Notes: This figure shows the S&P Kensho Drones Index from June 2013 to Feb 2020, at a daily frequency.

The S&P Kensho New Economies Composite index uses an entirely rules-based quantitative weighting algorithm to objectively uncover companies involved in the New Economies 21st Century Sectors. It is comprised of a dynamically adjusted list of companies drawn from all the Subsector Indices from nascent industries all the way through to maturity, presenting a balance between mainstream and cutting-edge companies as they shift their strategic focus to the 21st

[6] The S&P Kensho Drones Index is a subsector index provided by the S&P Kensho New Economy Index Series which includes the 21st Century Sectors that are propelling the Fourth Industrial Revolution and fostering new growing industries. Further information on S&P Kensho Drones Index is available at: https://www.spglobal.com/spdji/en/indices/equity/sp-kensho-drones-index/.

Century Sector technologies, driving the rise of the New Economy. The most prevalent use of the market for drones in the New Economy features both recreational and commercial aspects, predominantly with respect to non-military scopes. However, the main reason contributing to the popularization of drones is with regards its military applications thanks to their more sophisticated technology.

We select drone companies that are constituents of the S&P Kensho Drones Index as of 2019, namely the 24 stocks listed in Table A1. This allows us to cover a more extended time period (S&P Kensho Drones Index is only available from July 2013) and to investigate the impact of drone strikes on each company in the index.[7] The daily stock prices for the S&P Kensho Drones Index constituents are collected from Bloomberg. The drone companies daily implied volatility is obtained from the IvyDB OptionMetrics Volatility Surface file available through WRDS, updated to December 2019. The file provides Black-Scholes implied volatilities for options with standard maturities and delta levels.[8] We collect, for each underlying stock among the constituents of the S&P Kensho Drones Index, the at-the-money (ATM) options implied volatility for both calls and puts (absolute delta equal to 0.5) with 30-days to maturity for each underlying company.[9] Descriptive statistics of drone companies prices and implied volatilities are also available in Table A1 in the paper Appendix.

4 Event-Study Regressions

We assess the impact of drone strikes on the panel of drone companies via standard event-study regressions as follows:

$$\triangle IV_{t,k} = \alpha + \beta_{IV} \triangle IV_{t-1,k} + \beta_{Drone} D_{Drone,t-1} + \beta_{VIX} \triangle VIX_{t-1} + \epsilon_t \tag{1}$$

[7] We thank S&P Dow Jones Indices service for providing us the updated list of constituents of the S&P Kensho Drones Index. It includes multinational and large market capitalization companies such as Boeing Co., Nvidia Corp., and Lockheed Martin.

[8] The OptionMetrics volatility surface computes the interpolated implied volatility surface separately for puts and calls using a kernel smoothing algorithm using options with various strikes and maturities.

The volatility surface data contains implied volatilities for a list of standardized options for constant maturities and deltas. A standardized option is only included if there exists sufficient underlying option price data on that day to accurately compute an interpolated value. The interpolations are done each day so that no forward-looking information is used in computing the volatility surface. One advantage of using the volatility surface is that it avoids having to make potentially arbitrary decisions on which strikes or maturities to include in computing an implied call or put volatility for each stock.

[9] For information regarding this data set and reasons why put-call parity doesn't hold, see An et al. (2014).

where $IV_{t,k}$ is the call ATM implied volatility of one of the k drone companies at time t, $\triangle$ the log-difference operator, D_{Drone} a dummy indexed for every day there was a drone strike with at least 10 casualties, VIX_{t-1} represents the previous day S&P VIX index adopted as a control variable reflecting any other turbulent event which might have impacted on $IV_{t,k}$. We also control for the log difference of the previous lag of the dependent, namely $IV_{t-1,k}$. To examine the impact of drone strikes with respect to specific target countries and US presidents in office, we run the following multivariate event-study regressions:

$$\triangle IV_{t,k} = \alpha + \beta_{IV} \triangle IV_{t-1,k} + \sum_{i=1}^{4} \beta_{Country_i} D_{Country_i,t-1} + \beta_{VIX} \triangle VIX_{t-1} + \epsilon_t \tag{2}$$

$$\triangle IV_{t,k} = \alpha + \beta_{IV} \triangle IV_{t-1,k} + \sum_{j=1}^{3} \beta_{President_j} D_{President_j,t-1} + \beta_{VIX} \triangle VIX_{t-1} + \epsilon_t \tag{3}$$

where everything is as in equation 1, with the dummies now featuring either the four countries targeted with $i \in (Afghanistan, Somalia, Pakistan, Yemen)$ or the US presidents in office at the time of the strike with $j \in (Bush, Obama, Trump)$.

In addition to examining the impact of drone strikes on the implied volatility, we also further examine the impact on the drone companies stock prices. We replace the implied volatility in equations from 1 to 3 with the stock prices of the drone companies, the dependent variable being now the log difference of the price of one of the k drone companies at time t as follows:

$$\triangle P_{t,k} = \alpha + \beta_P \triangle P_{t-1,k} + \beta_{Drone} D_{Drone,t-1} + \beta_{VIX} \triangle VIX_{t-1} + \epsilon_t \tag{4}$$

where everything is as in equation 1, with now $\triangle P_{t,k}$ being the difference in logarithm of each of the k drone companies price at time t. We then also run multivariate equations with respect to each country targeted and US president, replacing the dependent variable with the log difference of the drone companies prices.

$$\triangle P_{t,k} = \alpha + \beta_P \triangle P_{t-1,k} + \sum_{i=1}^{4} \beta_{Country_i} D_{Country_i,t-1} + \beta_{VIX} \triangle VIX_{t-1} + \epsilon_t \tag{5}$$

$$\triangle P_{t,k} = \alpha + \beta_P \triangle P_{t-1,k} + \sum_{j=1}^{3} \beta_{President_j} D_{President_j,t-1} + \beta_{VIX} \triangle VIX_{t-1} + \epsilon_t \tag{6}$$

where everything is as in equation 4, and dummies as in equation 2 and 3.

5 Empirical Results

This section reports the empirical results with respect to the impact of the drone strikes dummy variables on the implied volatility of the individual stocks of the constituents of the S&P KDRONES Index (subsection 5.1) and on the price of individual stocks of the constituents of the S&P KDRONES Index (subsection 5.2).

5.1 Drone Strikes on Drone Companies Implied Volatility

In Table 1 we present the empirical results on the impact of the drone strikes on the ATM call implied volatility of each one of the S&P Kensho Drones Index 24 constituents. We observe that a drone strike is found to significantly increase the next day implied volatility of the drone companies in 17 cases out of our sample of 24. We repeated the analysis by considering dummy variables capturing only drone strikes featuring a higher number of casualties, namely at least 20, 30 and 50, finding a significant impact in 8, 10 and only 2 cases, respectively. Such a finding suggests that the number of casualties is not the main reason of the significant impact of drone strikes on the drone companies implied volatility.

Table 1: Drone Strikes on Drone Companies Implied Volatility: All Strikes

	AMBA	AVAV	BA	CMTL	CUB	ESTL	FET	FLIR	FTI	GD	HEI	HII
Drone	1.45***	1.01	1.27**	1.53**	1.56	-0.86	0.03*	1.40**	1.51***	1.21***	0.23	1.70***
	(0.53)	(0.82)	(0.50)	(0.75)	(1.43)	(2.17)	(0.01)	(0.68)	(0.54)	(0.44)	(0.29)	(0.58)
Adj. R^2	3.8	14.9	2.8	12.3	24.8	17.6	17.1	11.3	6.8	2.5	18.6	7.3
	HRS	IRDM	KTOS	LLL	LMT	MRCY	NOC	NVDA	RTN	TDG	TDY	TXT
Drone	0.09*	3.54***	0.34	1.53***	0.99**	1.55	0.83*	1.65***	1.02**	1.91***	1.18	1.59***
	(0.05)	(0.95)	(1.37)	(0.47)	(0.45)	(1.27)	(0.46)	(0.45)	(0.44)	(0.72)	(1.05)	(0.48)
Adj. R^2	7.2	21.7	12.6	5.2	5.4	18.3	2.3	1.7	3.4	6.9	22.1	1.1

Notes: This table presents results of event-study based regressions run through equation 1 where the 24 S&P Kensho Drones Index drone companies implied volatility log difference (in percentage) is regressed onto drone strikes dummy variable tracking strikes featuring at least 10 fatalities. We control for the previous lag of the dependent implied volatilities and previous lag of the VIX index. Coefficients, standard error (in parentheses), and adjusted R^2 (in percentage) with respect to the drone strikes dummy are reported. Coefficients for controls are omitted to save space. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Period from 02-01-2006 to 31-12-2019, daily frequency.

We suggest that the main reason may rather be due to the target countries, as well as the US president in office, hence we present here the results of the multilateral event study regressions in which the dummy variable is disentangled according to the target country only (Table 2) and to the US president only (Table 3). We observe that a drone strike in Afghanistan positively impacts the next day implied volatility of drone companies in 15 cases out of 23 available. A drone strike in Somalia and Pakistan shows a significant impact on the next day drone companies implied volatility in 6 and 8 cases out of 23 available, respectively, while in Yemen in 11 cases out of 24. Most of the time we detect a positive association between drone strikes in these countries and the implied volatility of the drone companies.

Table 2: Drone Strikes on Drone Companies Implied Volatility: Strikes by Country

	AMBA	AVAV	BA	CMTL	CUB	ESTL	FET	FLIR	FTI	GD	HEI	HII
Afghanistan	1.89***	1.71*	1.83***	1.56*	2.56	NA	1.94	1.62*	2.50***	2.00***	2.58	0.23***
	(0.61)	(0.90)	(0.69)	(0.94)	(2.00)	NA	(2.17)	(0.94)	(0.88)	(0.61)	(3.43)	(0.07)
Somalia	0.38	0.50	-4.59*	2.68	-3.38	NA	6.58*	-1.76	-3.10	0.28	-5.20	0.19
	(1.27)	(3.09)	(2.57)	(2.14)	(4.09)	NA	(4.11)	(1.94)	(3.39)	(1.26)	(6.31)	(0.14)
Pakistan	-1.32	-0.89	-1.77**	1.01	-0.10	-1.29	1.44*	1.05	-2.32**	0.21	NA	0.01
	(4.17)	(1.58)	(0.89)	(1.47)	(0.28)	(2.23)	(0.86)	(1.33)	(0.97)	(0.86)	NA	(0.22)
Yemen	0.91	2.78	2.61*	0.62	9.44**	5.05	3.99	5.22***	1.28	1.53	-1.99*	-0.10
	(2.23)	(2.39)	(1.37)	(2.23)	(4.28)	(9.21)	(6.36)	(2.02)	(1.60)	(1.32)	(1.13)	(0.16)
Adj. R^2	3.7	14.7	2.8	12.2	24.9	17.5	17.1	11.5	6.9	2.6	18.5	7.2
	HRS	IRDM	KTOS	LLL	LMT	MRCY	NOC	NVDA	RTN	TDG	TDY	TXT
Afghanistan	0.07	4.15***	1.11	1.89***	1.18**	0.69	0.76	2.06***	1.38**	2.13**	-0.43	1.54**
	(0.08)	(1.26)	(2.14)	(0.65)	(0.60)	(1.74)	(0.64)	(0.64)	(0.62)	(1.00)	(1.43)	(0.67)
Somalia	0.05	4.29*	0.15	2.72**	0.47	2.09	2.21*	0.91	0.48	1.07	2.84	2.46*
	(0.16)	(2.57)	(7.46)	(1.37)	(1.28)	(4.71)	(1.32)	(1.31)	(1.27)	(2.05)	(3.88)	(1.38)
Pakistan	0.21**	-1.73	3.17*	0.41	1.73**	-0.05	0.81	1.32*	-0.19	1.76*	1.43	0.49
	(0.11)	(2.37)	(1.95)	(0.92)	(0.88)	(2.43)	(0.91)	(0.80)	(0.87)	(1.13)	(2.00)	(0.95)
Yemen	0.35**	5.48**	-3.35	0.90	1.24	6.25*	1.95	2.02*	2.81**	2.36	6.50**	2.66*
	(0.17)	(2.68)	(3.53)	(1.40)	(1.34)	(3.79)	(1.38)	(1.16)	(1.33)	(2.14)	(3.05)	(1.44)
Adj. R^2	7.3	21.7	12.6	5.2	5.4	18.5	2.2	1.6	3.5	6.7	22.1	1.1

Notes: This table presents results of the event-study based regressions run through equation 2 where the 24 S&P Kensho Drones Index drone companies implied volatility log difference (in percentage) is regressed onto drone strikes dummy variable tracking strikes featuring at least 10 fatalities and divided by target country of the strike, namely Afghanistan, Somalia, Pakistan and Yemen. We control for the previous lag of the dependent implied volatilities and previous lag of the VIX index. Coefficients, standard error (in parentheses), and adjusted R^2 (in percentage) with respect to the drone strikes dummy are reported. Coefficients for the controls are omitted to save space. NA indicates company implied volatility unavailable. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The period is from 02-01-2006 to 31-12-2019, at daily frequency.

With respect to the US president in office at the time of the strike, we uncover evidence showing that drone strikes under the Bush presidency are found to be significantly and positively impacting the next day drone companies implied volatility in 14 out of the 19 available cases (due to data availability), and under president Obama in 16 cases out of 24.[10] In only 5 drone companies (out of 21 available) do we find that the implied volatility is affected by president Trump drone strikes campaign. This might be explained by the fact that only recently, president Trump has extended the use of drones beyond traditional conflict zones, broadening the war on terror into Yemen and Somalia.

A stronger statistical significance on the impact of drone strikes under president Bush or Obama may suggest a *desensitivity* of drone companies to strikes, being able to better incorporate news surrounding violence and geopolitical risk more efficiently. Drone strikes during earlier years, especially soon after 9/11 might have triggered investors' sentiment in a greater way compared to more recent strikes, significantly increasing drone companies implied volatility. This suggests evidence towards a possible resilience rationale, similar to the terrorist attacks literature (e.g., see Chen and Siems, 2004; Bevilacqua et al., 2020).

[10]Under the administration of president Obama, drone strikes proliferated as a means of fighting counter-insurgency, recognizing the advantages associated with drone strikes of not having to risk military personnel on dangerous air missions in countries such as, for e.g. Afghanistan.

Table 3: Drone Strikes on Drone Companies Implied Volatility: Strikes by President

	AMBA	AVAV	BA	CMTL	CUB	ESTL	FET	FLIR	FTI	GD	HEI	HII
Bush	NA	6.49*	3.15*	4.88*	7.56*	0.63	NA	3.15	0.70***	3.19**	NA	NA
	NA	(3.37)	(1.77)	(2.83)	(4.12)	(3.63)	NA	(2.57)	(0.18)	(1.62)	NA	NA
Obama	1.70***	0.93	1.22**	1.59*	2.35	-1.76	2.58	1.60*	0.09*	1.35***	5.01	1.64**
	(0.71)	(0.99)	(0.57)	(0.94)	(1.81)	(2.69)	(2.39)	(0.85)	(0.05)	(0.52)	(4.50)	(0.74)
Trump	1.15*	0.06	0.81	0.65	-1.08	NA	4.00*	0.45	NA	0.42	1.56	1.54*
	(0.65)	(1.55)	(1.31)	(1.30)	(2.48)	NA	(2.41)	(1.17)	NA	(0.76)	(3.72)	(0.89)
Adj. R^2	3.7	14.9	2.7	12.3	24.8	17.3	17.1	11.3	7.1	2.5	18.6	7.1
	HRS	IRDM	KTOS	LLL	LMT	MRCY	NOC	NVDA	RTN	TDG	TDY	TXT
Bush	0.36*	NA	2.96	4.84***	4.97***	-0.30	4.03**	5.90***	3.42**	6.33**	2.79	4.16**
	(0.21)	NA	(4.14)	(1.78)	(1.70)	(0.47)	(1.75)	(1.73)	(1.68)	(2.95)	(3.87)	(1.83)
Obama	0.12*	4.21***	0.10	1.72***	1.17**	0.21	1.05*	1.45**	1.26**	2.13***	1.59	1.91***
	(0.07)	(1.18)	(1.46)	(0.59)	(0.56)	(0.15)	(0.58)	(0.57)	(0.56)	(0.90)	(1.29)	(0.61)
Trump	0.07	2.76*	NA	0.29	-0.14	0.11	-0.34	2.05***	-0.09	0.52	0.17	0.46
	(0.10)	(1.56)	NA	(0.82)	(0.78)	(0.24)	(0.80)	(0.79)	(0.77)	(1.24)	(1.97)	(0.83)
Adj. R^2	7.3	21.7	12.6	5.3	5.6	18.2	2.3	1.8	3.4	6.8	21.9	1.4

Notes: This table presents results of the event-study based regression run through equation 3 where the 24 S&P Kensho Drones Index drone companies implied volatility log difference (in percentage) is regressed onto drone strikes dummy variable tracking strikes featuring at least 10 fatalities and divided by US president in office at the time of the strike, namely Bush, Obama and Trump. We control for the previous lag of the dependent implied volatilities and previous lag of the VIX index. Coefficients, standard error (in parentheses), and adjusted R^2 (in percentage) with respect to the drone strikes dummy are reported. Coefficients for the controls are omitted to save space. NA indicates company implied volatility unavailable. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The period is from 02-01-2006 to 31-12-2019, at daily frequency.

We also relate our findings to a possible geopolitical risk explanation given that in the majority of cases, regardless the dummy adopted, a drone strike is generally associated with an increase in implied volatility. The country targeted and the US president in office are found to be valid proxies for drawing some lines on possible geopolitical consequences of the strikes. The positive relationship between the strikes and the drone company volatility may suggest that drone strikes can lead to an increase in political tension and risk of retaliation from the targeted countries. For instance, Jaeger and Siddique (2018) state that in Pakistan, the probability of a terrorist attack increases in the first week following a drone strike.[11]

In only a few cases related to some of the countries targeted might we adopt an alternative hypothesis, namely viewing drone strikes as a counter-terrorism weapon, given we detect more mixed results regarding the coefficients signs. While this explanation does not find correspondence in the signs of the coefficients associated with the US presidents, it may however be adopted with respect to specific countries and operations where we observe more varied results in terms of the signs of the coefficients. In fact, in line with the discussion in Naveed et al. (2017), the reaction of the drone companies volatility to the drone strikes may depend on the type of strike, its circumstances, and potential consequences.

However, to validate the geopolitical rationale that we put forward with respect to our findings, we show that such counter-terrorist effects is not peculiar to drone strikes. We consider probably the most known US counter-terrorism event, namely the killing of Osama Bin Laden

[11]For example, after a terrorist attack on a police academy in Lahore in March 2009 in which 18 people were killed, Baitullah Mehsud (then leader of the Tehrik-e-Taliban Pakistan) stated that the attack was "in retaliation for the continued drone strikes by the United States in collaboration with Pakistan on our people" (see Jaeger and Siddique, 2018).

on the 2nd May 2011. After President Barack Obama's announcement of the death of Osama Bin Laden, the S&P 500 grew by only 0.5 percent in the intra-daily market session soon after opening on Monday. Stock market prices even fell by the end of the trading day and in the following days.[12] These results indicate a negative impact of the killing of Osama Bin Laden on the US stock market, raising questions about the role of the war of terrorism. For similar findings with respect to the Pakistani stock market see Afik et al. (2016).

According to the New York Times: "Compared to the enormous political and psychological significance of Bin Laden's death, the stock market reaction was relatively muted." Moreover, the financial response to the news did not mirror the response to the 9/11 terrorist attacks when the markets closed for two days, and on reopening dropped by a few percentage points (e.g., see Burch et al., 2016; Papakyriakou et al., 2019; Bevilacqua et al., 2020). The possible difference among these two, almost opposite, reactions lies in the fact that the war on terror began on 9/11, but did not end with the death of Bin Laden. People believe that the war on terror is far from over and they do not expect that resources directed towards the war on terror to immediately be diverted back to the economy. Moreover, Al-Qaida threatens geopolitical uncertainty, terrorism and political risk, and the death of its leader may be interpreted as an easing of such threats. As confirmed from our findings, an overall increase in the volatility of drone companies may be connected to the fact that financial markets do not simply evaluate the cost/benefit of the strikes today, but also incorporate the effects of the strikes on the possible intensification of geopolitical risk and future conflicts.

Lastly, we also check the previous lags of the dummy variables in the event-study regressions, however we do not find any impact on the drone companies implied volatility beyond the second day following the drone strike. Investors appear to perceive them as one-off events that are unlikely to reoccur in the (near) future. We also control for the previous lag of the S&P 500 index instead of the VIX index, finding that the results hold materially the same.

5.2 Drone Strikes on Drone Companies Prices

The results from investigating the impact of drone strikes on the price of the S&P Kensho Drones Index constituents through equation 4 are reported in Table 4. We observe that a

[12]We observe that this led to a negative impact on the S&P 500 index which decreased from a price of 1363.61 on the 29th April to 1361.22 on the 2nd May, and decreased even more in the days afterwards (1356.62, 1347.32 and 1335.1 on the 3rd, 4th and 5th May, respectively). An opposite pattern is observed for the VIX index which increased from 14.75 on the 29th April to 15.99 on the 2nd May up to 18.2 on the 5th May.

day with a drone strike significantly impacts the next day stock prices in 15 cases out of 24 within our sample. In addition, among these, in only 4 cases do we find a drone strike related to a significant increase of the price of the drone stocks, while in the remaining 11 cases it is associated with a decrease in the next day's stock price. We corroborate the positive relationship found between drone strikes and implied volatility since, on average, drone strikes are found to decrease drone companies prices, in line with the well-known inverse relationship between stock price and stock volatility (see Whaley, 2009). We have also considered the second day price changes following the strike, finding that in some cases the impact is still significant. This impact is not found to last beyond the second day in any of the cases, therefore can be seen as being short lived.

Table 4: Drone Strikes on Drone Companies Prices: All Strikes

	AVAV	AMBA	BA	CMTL	CUB	ESTL	FLIR	FET	GD	HEI	HRS	HII
Coeff	0.05**	-0.12	-0.28**	0.06	-0.29*	-0.24*	-0.30**	-0.49*	-0.02*	0.03**	0.01	-0.06
	(0.02)	(0.29)	(0.13)	(0.18)	(0.17)	(0.13)	(0.15)	(0.28)	(0.01)	(0.01)	(0.13)	(0.13)
Adj. R^2	0.3	0.2	0.4	0.2	0.8	1.2	0.5	1.4	0.2	0.5	13.2	0.4
	IRDM	KTOS	LLL	LMT	MRCY	NOC	NVDA	RTN	FTI	TDY	TXT	TDG
Coeff	-0.48***	0.61**	0.01	-0.08	0.43**	0.02	-0.41**	0.01	-0.53***	-0.20*	-0.01	-0.31**
	(0.18)	(0.24)	(0.10)	(0.09)	(0.21)	(0.10)	(0.20)	(0.10)	(0.18)	(0.11)	(0.20)	(0.14)
Adj. R^2	0.3	0.5	0.2	0.5	0.6	0.5	0.2	0.2	0.6	0.7	0.2	0.3

Notes: This table presents results of event-study based regressions run through equation 4 where the 24 S&P Kensho Drones Index drone companies price log returns (in percentage) is regressed onto drone strikes dummy variable tracking strikes featuring at least 10 fatalities. We control for the previous lag of the dependent stock prices and previous lag of the VIX index. Coefficients, standard error (in parentheses), and adjusted R^2 (in percentage) with respect to the drone strikes dummy are reported. Coefficients for controls are omitted to save space. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Period from 02-01-2006 to 31-12-2019, daily frequency.

We report in table 5 the results of the multivariate equation 5 with respect to the impact of country specific drone strikes on company prices. Our results show that Afghanistan is found to be significant in 7 cases out of 24, Somalia in 5 cases out of 24, Pakistan in 10 cases, while Yemen in 11 cases. Afghanistan, Pakistan and Yemen are most predominant in impacting the next day drone companies returns, presenting mostly negative coefficients when significant. We confirm evidence that drone strikes against these countries show slightly higher significance, possibly coherent with the resilience hypothesis for Pakistan or could be due to a specific target or operation running in such countries. We think this might be due to the fact that Pakistan has been target of drone strikes mainly between 2006 and 2013, Afghanistan mainly after 2015, Somalia predominantly in recent years and Yemen all the way throughout our sample from 2010, though the number of strikes are less. This suggests evidence that those countries targeted in the earlier years of our sample show slightly higher significance, possibly coherent with the resilience hypothesis put forward in the literature studying terrorist attacks and stock markets. Our results with respect to the drone companies stock prices are also in line with Naveed et al. (2017), who find that the initial reaction of the equity market to counter terrorism is often negative after the news breaks, reflecting the panic of investors and an increase in general uncertainty about the market. The market shows a gradual revival once the event and its initial consequences are disclosed and analyzed.

Table 5: Drone Strikes on Drone Companies Prices: Strikes by Country

	AVAV	AMBA	BA	CMTL	CUB	ESTL	FLIR	FET	GD	HEI	HRS	HII
Afghanistan	0.50**	0.02	0.03**	0.08	-0.22	0.03	0.03	-0.25	-0.02	-0.05	-0.35**	-0.01
	(0.25)	(0.34)	(0.18)	(0.26)	(0.24)	(0.18)	(0.21)	(0.33)	(0.15)	(0.22)	(0.15)	(0.16)
Somalia	0.10	0.06	0.05	-0.04	-0.37	0.09**	-0.02	-1.09*	0.06	0.17	0.32	-0.21
	(0.58)	(0.70)	(0.03)	(0.54)	(0.49)	(0.04)	(0.43)	(0.60)	(0.30)	(0.46)	(0.39)	(0.33)
Pakistan	0.68*	-1.21	-0.05**	-0.07	0.48*	-0.07**	-0.64**	-0.69	-0.34*	-0.53*	-0.12	-0.30
	(0.41)	(2.29)	(0.02)	(0.37)	(0.30)	(0.02)	(0.30)	(1.32)	(0.20)	(0.32)	(0.26)	(0.49)
Yemen	-0.44	-1.81*	-0.05*	-0.05	-0.46	-0.06*	-1.02**	-2.02**	-0.69**	0.11	-0.16	-0.10
	(0.59)	(1.03)	(0.03)	(0.05)	(0.50)	(0.03)	(0.44)	(0.92)	(0.31)	(0.47)	(0.39)	(0.35)
Adj. R^2	0.3	0.2	0.4	0.2	0.8	1.3	0.7	1.5	0.4	0.6	1.3	0.5
	IRDM	**KTOS**	**LLL**	**LMT**	**MRCY**	**NOC**	**NVDA**	**RTN**	**FTI**	**TDY**	**TXT**	**TDG**
Afghanistan	-0.05**	-0.55*	0.01	0.04	-0.50*	0.12	-0.28	0.02	-0.39*	-0.06	0.09	-0.38**
	(0.02)	(0.34)	(0.14)	(0.13)	(0.32)	(0.14)	(0.30)	(0.14)	(0.21)	(0.19)	(0.28)	(0.19)
Somalia	0.08*	-0.19	0.46*	0.13	0.21	-0.17	0.19	-0.02	-0.13	-0.24	-0.01	0.59*
	(0.05)	(0.69)	(0.28)	(0.28)	(0.67)	(0.30)	(0.63)	(0.02)	(0.53)	(0.39)	(0.06)	(0.41)
Pakistan	0.03	0.73*	-0.03	-0.43***	0.47	0.09	-0.08	0.07	-0.67**	-0.28	0.03	-0.26
	(0.04)	(0.44)	(0.20)	(0.15)	(0.45)	(0.20)	(0.43)	(0.19)	(0.32)	(0.27)	(0.04)	(0.28)
Yemen	-0.02	-2.68*	-0.42	-0.26	-1.61**	-0.51*	-0.49	-0.02	-1.57***	-0.34	-0.08*	-0.49
	(0.05)	(1.53)	(0.31)	(0.29)	(0.72)	(0.31)	(0.64)	(0.02)	(0.54)	(0.40)	(0.05)	(0.41)
Adj. R^2	0.3	0.4	0.4	0.7	0.8	0.2	0.2	0.3	0.8	0.8	0.2	0.4

Notes: This table presents results of the event-study based regressions run through equation 5 where the 24 S&P Kensho Drones Index drone companies price log returns (in percentage) is regressed onto drone strikes dummy variable tracking strikes featuring at least 10 fatalities and divided by target country of the strike, namely Afghanistan, Somalia, Pakistan and Yemen. We control for the previous lag of the dependent stock prices and previous lag of the VIX index. Coefficients, standard error (in parentheses), and adjusted R^2 (in percentage) with respect to the drone strikes dummy are reported. Coefficients for the controls are omitted to save space. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The period is from 02-01-2006 to 31-12-2019, at daily frequency.

With respect to the US presidents (multivariate equation 6), the results, as reported in table 6, show that drone strikes under president Bush are found to significantly impact drone companies prices the most, 17 cases out of 21 (due to data availability), mainly with a decreasing effect. Drone strikes under president Obama and president Trump are found to significantly impact drone companies in 8 cases out of 24. These findings further confirm the resilience rationale given that drone strikes during earlier years were impacting on the stock market to a greater extent compared to more recent years. The alternative argument that drone strikes closer to 9/11 might have been seen as a counter-terrorism weapon is however not consistent with the results we find. For such argument to hold we would rather expect a positive relationship between drone strikes and drone companies prices. This does not correspond with the sign of the coefficients we detect, be it negative, associated to the drone strikes under the incumbent president at the time, namely president Bush. The findings of decreasing stock prices after the drone strikes are counterintuitive for a *calming* counter-terrorist operation.[13]

[13] Also with respect to the drone companies stock prices we checked the impact of the previous lags of the drone strike dummy variables. The results are in line to the ones obtained for the drone companies implied volatility, namely the strikes impact being short lived and not lasting beyond the second day following the strike. Also in this regression we have controlled for the previous lag of the S&P 500 index instead of the VIX with the results holding the same.

Another explanation may lie on the increasing geopolitical risk. This would be consistent with president Bush's years of office and in line with the countries involved such as Pakistan and Yemen. Results with respect to the drone companies implied volatility corroborate this geopolitical risk hypothesis since we detect an increase in implied volatility connected to president Bush as well as countries such as Afghanistan and Yemen. These results also appear to draw close to the variance led by war-related news (or war risk factor) hypothesis in Rigobon and Sack (2005), in which the effects of the risks associated with the war in Iraq, for example the days in which President Bush addressed the nation regarding the war, translate to increases in war risk causing declines in equity prices. Similarly, days in which we witness drone strikes may increase investors' perceptions of an increased geopolitical risk, reflected in falls in equity prices.

Table 6: Drone Strikes on Drone Companies Prices: Strikes by President

	AVAV	AMBA	BA	CMTL	CUB	ESTL	FLIR	FET	GD	HEI	HRS	HII
Bush	-0.25***	NA	-0.13***	-0.10*	-1.05*	-0.18***	-1.51***	NA	-1.41***	-1.36**	1.80***	NA
	(0.08)	NA	(0.04)	(0.06)	(0.64)	(0.04)	(0.56)	NA	(0.39)	(0.60)	(0.52)	NA
Obama	0.03*	-0.48	-0.02*	-0.01	-0.01	-0.01	-0.14	-0.53*	-0.20*	0.06	0.43**	-0.13
	(0.02)	(0.39)	(0.01)	(0.02)	(0.21)	(0.02)	(0.19)	(0.32)	(0.13)	(0.20)	(0.17)	(0.16)
Trump	0.05*	0.17	0.04**	0.05*	-0.15	0.02	-0.05	-0.56*	0.06	0.20	0.32*	0.02
	(0.03)	(0.41)	(0.02)	(0.03)	(0.29)	(0.02)	(0.25)	(0.31)	(0.18)	(0.27)	(0.18)	(0.19)
Adj. R^2	0.6	0.2	0.5	0.3	0.8	1.5	0.9	1.3	0.6	0.8	1.3	0.4

	IRDM	KTOS	LLL	LMT	MRCY	NOC	NVDA	RTN	FTI	TDY	TXT	TDG
Bush	-0.09	0.14	-0.96***	-1.55***	-0.02	-0.65*	-0.83	-0.66**	-3.25***	-1.72***	-1.68**	-2.14***
	(0.08)	(0.89)	(0.37)	(0.37)	(0.08)	(0.39)	(0.82)	(0.33)	(0.68)	(0.51)	(0.76)	(0.54)
Obama	-0.01	0.10	-0.04	-0.04	0.01	0.03	-0.39*	0.05	-0.36*	-0.02	0.15	-0.23*
	(0.02)	(0.30)	(0.13)	(0.12)	(0.02)	(0.13)	(0.22)	(0.12)	(0.21)	(0.17)	(0.26)	(0.12)
Trump	0.07**	1.21***	0.30	0.12	0.01	0.09	0.21	0.02	-0.44*	-0.04	-0.04	-0.06
	(0.03)	(0.42)	(0.18)	(0.16)	(0.04)	(0.18)	(0.37)	(0.17)	(0.28)	(0.23)	(0.35)	(0.24)
Adj. R^2	0.3	0.5	0.5	1	0.6	0.2	0.3	0.5	1.2	1.1	0.3	0.8

Notes: This table presents results of event-study based regressions run through equation 6 where the 24 S&P Kensho Drones Index drone companies price log returns (in percentage) is regressed onto drone strikes dummy variable tracking strikes featuring at least 10 fatalities and divided by US president in office at the time of the strike, namely Bush, Obama and Trump. We control for the previous lag of the dependent stock prices and previous lag of the VIX index. Coefficients, standard error (in parentheses), and adjusted R^2 (in percentage) with respect to the drone strikes dummy are reported. Coefficients for the controls are omitted to save space. NA indicates company implied volatility unavailable. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The period is from 02-01-2006 to 31-12-2019, at daily frequency.

In the next section we carry out a number of robustness checks to determine whether these baseline results persist when we vary the company related or US financial market related dependent variable, or when we control for additional market factors.

6 Additional Robustness Checks

6.1 Drone Companies Put Options Implied Volatility

We further study the impact of drone strikes on the implied volatility of drone companies, this time extracted from ATM put options. We now consider $IV_{t,k}$ as the put ATM implied volatility of one of the k drone companies at time t in equations from 1 to 3.[14] We detect a significant impact of the dummy featuring drone strikes with at least 10 fatalities in 14 out of the 24 cases. The impact when using ATM implied volatility extracted from options is also confirmed to be positive overall, when found to be significant. When we look at the specific countries targeted by the drone strikes, we find a similar picture as for drone companies ATM call implied volatility. In fact, a drone strike in Afghanistan shows a significant impact on the drone companies ATM put implied volatility in 15 out of 23 cases, in Somalia and Pakistan in 6 and 7 out of 23 cases available, respectively, and in Yemen in 9 out of the 24 cases. Again, as found for the call implied volatility, most of the time we find a positive impact of drone strikes on the put implied volatility of the drone companies. With respect to the US president, we find that drone strikes under president Bush significantly and positively affect the ATM put implied volatility of drone companies in 11 out of the 19 available cases (due to data availability). Drone strikes under president Obama are found to be significantly and positively affecting the next day implied volatility in 11 out of 24 cases, while under president Trump in 5 out of 21 cases. Therefore, overall we find that, even though weaker in significance, the results lead to the same conclusions, thereby corroborating the geopolitical risk and resiliency explanations drawn from the previous sections.

6.2 Drone Strikes on Broader Stock Market Indices

Additionally, we examine the impact of drone strikes directly on the S&P Kensho Drones Index log price returns. We observe that the index returns decrease the day after a drone strike, the coefficient showing significance at the 1% level with a negative sign.[15] Dummies with respect to the countries targeted and the US president in office also show a significant negative impact on the next day S&P Kensho Drones Index returns, recognizing however that this index is only available starting from mid-2013. Finally, we extend the analysis to the broader US stock market, looking at the impact of drone strikes on the S&P 500 and VIX index. We corroborate our findings, detecting a significant negative (positive) impact of the drone strikes dummy variable with respect to S&P 500 Index (VIX Index). The VIX represents the market participants' best collective estimate of the realized volatility of the underlying equity index

[14] The whole set of results with respect to ATM put options is reported in the paper Appendix.

[15] We have checked the impact of dummy variables capturing only drone strikes featuring a higher number of casualties, namely at least 20 and at least 50, finding no significant impact on the next day S&P Kensho Drones Index returns, hence confirming the evidence that disentangling strikes by targeted countries and US president matters more for the index prices to react.

over the next 30 calendar days. The level of VIX depends directly on the prices of the options and it fully embodies both the fear and exuberance of a diverse set of market participants. It can be considered an excellent measure of market sentiment linking the market perception of risk and current market conditions (see Low, 2004; Fassas and Papadamou, 2018). In terms of countries, we detect a significant impact for Pakistan, while regarding presidents a significant impact for Bush and Obama is detected, with the direction of the impact confirming the same conclusion as that drawn for the drone companies.[16]

6.3 Controlling for the Fama-French Factors

In this robustness exercise we verify whether or not the impact of the drone strikes hold upon the inclusion of the Fama and French (2017) five factors.[17] The five factors include the market excess return (ER), the average return on value portfolios minus average return on growth portfolios (HML), the average return on small portfolios minus average return on big portfolios (SMB), the average return on the two robust operating profitability portfolios minus the average return on the two weak operating profitability portfolios (RMW), and the average return on the two conservative investment portfolios minus the average return on the two aggressive investment portfolios (CMA).[18] We incorporate the Fama and French (2017) five factors as controls in the regression equations 1 to 3 discussed in Section 4. Hence, we take into account the drone strikes dummies, the previous lag of the dependent variables, the previous lag of VIX and also control for the lagged Fama-French factors.

Tables B4 to B6 in the paper Appendix present the results of the robustness checks regarding the drone companies implied volatility. We observe that, in most cases, the regressions' adjusted R^2s improve because of the additional information from the factors included in the model. However, the significance of the drone strikes still hold even after including the additional five factors as controls. We confirm that a drone strike significantly increases the next day drone companies implied volatility in 17 cases out of 24. Regarding the targeted countries, drone strikes in Afghanistan, Somalia and Pakistan impact the next day implied volatility of drone companies in 15, 5, and 7 cases out of 23 available, respectively, while in Yemen in 10 cases out of 24. Even though these findings account for one less statistically significant company for these

[16]The results with respect to these brief empirical exercises are available from the authors upon request.

[17]According to Fama and French (2017), a model including the five factors is found to perform better than the traditional Fama and French (1993) three-factor model.

[18]For further details on the methodology for computing these five factors see Kenneth R. French Data Library at: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html from where the data is collected.

three targeted countries compared to the baseline model, and the coefficients' significance is, at times, reduced at the 10% level, we still confirm the significant impact of the drone strikes in these countries. With respect to the US presidents, when controlling for the five factors, drone strikes under the Bush presidency are still found to impact the drone companies implied volatility in 14 out of the 19 available cases, under president Obama in 16 of the 24 cases and president Trump in only 5 of the 21 available cases, therefore confirming our previous findings.

We also repeat the same robustness checks with respect to drone company prices adding the Fama-French five factors in regression equations 4 to 6. The results are reported in Tables B7 to B9 in the paper Appendix. We observe that drone strikes significantly impact the next day stock prices in 14 cases out of 24. A drone strike in Afghanistan, Somalia, Pakistan and Yemen still impacts drone company prices in 7, 4, 6, and 7 cases out of 24, respectively. The dummy variables related to the country of the strike slightly reduce in significance when adding the five factors as controls. With respect to the US presidents, we observe that strikes under president Bush significantly impact drone company prices in 17 cases out of 21, with significance in a few cases reduced to the 10% level. Drone strikes under president Obama and president Trump are now found to significantly impact drone company prices in only 5 and 7 cases out of 24, respectively.[19] While the results hold materially the same with respect to the drone companies implied volatility, the significance of our findings for a few drone companies prices is found to be slightly reduced or, in some cases, absent when we control for the five Fama-French factors, especially with respect to the targeted country and US president.[20]

This robustness exercise shows the importance of the Fama-French five factors more as drivers of drone company prices rather than implied volatility. Adding the five factors weakened, in some cases, the significant impact of the drone strikes on drone company prices. The five factors appear to contain useful information in explaining drone stock prices, possibly being related to their fundamentals, materializing in an increased regressions' adjusted R^2s and a reduced significance of the drone strike dummies. In contrast, the significance of the drone strikes for the implied volatility of the drone companies still hold even after controlling for the five factors. This further corroborates our intuition with respect to the role of drone strikes as

[19]With respect to the drone companies returns, we also adopted the excess returns as our dependent variable computed as the log difference between the drone companies returns and the Fama and French (1993) risk-free rate of 1m T-Bill, however this led to materially the same results.

[20]As a further check, we repeated the same robustness checks described in this subsection adopting the Fama and French (1993) traditional three-factor model. The results are found to be materially the same and are available from the authors upon request.

determinants of market sentiment and investors' fears. They contain a different set of information compared to the five factors when it comes to explaining market sentiment and volatility in line with our rationale of geopolitical risk and increased investors' fear related to the strikes.

7 Concluding Remarks

We have provided first evidence of an overall positive impact of drone strikes on the implied volatility of US drone companies. We show that US-led drone strikes on foreign soil *do* matter for the implied volatility of stocks in the growing drone industry, albeit the effect is short lived, not lasting beyond the second day after the strike. We show that the number of fatalities is not a sign of most significant strikes. Through a specific target country and president in office analysis, our findings draw towards a resilience rationale and possible geopolitical risk explanation. Several robustness checks corroborate our findings.

Overall, drone companies can be considered volatile due to their association with boom and growth contributing to the so called fourth industrial revolution, however, we detect first evidence showing that part of their volatility is driven by drone strikes, contributing in a few cases to a decline in the stock price of these companies, even if short-lived. Finally, we uncover a resilience pattern which may be viewed as comforting, however, as the current US administration has recently shown with the nature of the attack on general Soleimani, the ability to use the precision capability of drones to carry out high-target assassinations could escalate and mark a new chapter in US drone wars, with the risk of re-sensitizing the stock market to drone strikes.

Over the coming years drone companies will certainly grow and profit from the rise in drone commercial use. However, these profits may be offset by the increasing and more lethal use of drones as weapons for military purposes, leading to losses, increased stock volatility and damage to drone companies' reputation and image. This paper has shown that the latter could impact upon investors' fears through the options market volatility on drone companies, possibly affecting these companies' profits and reputation. Our analysis could be used to inform policy actions and decisions at the drone company level. There is capacity for unintended consequences resulting from drone strikes for drone companies due to the geopolitical risk factor that should neither be ignored nor left to prevail. Regulators and senior executives must ensure that the reputation risk to drone companies triggered by their involvement in the war on terror is avoided so that the economic benefits prevail. Greater emphasis should be focused in areas with more business success, in developing better company communication, in the use of tools to control the brand/company reputation amid images associated with the US military strikes and casualties, and also on a response plan to keep company stock volatility low and to sustain revenues and stock prices driven by the economic boom of the drone industry. The new commercial drone boom success should not be impeded by the risk it faces through its association with its use in the war on terror.

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The authors report no declarations of interest.

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Appendix

Appendix A Drone Companies

Table A1: S&P Kensho Drone Companies: Descriptive Statistics

		Stock Prices				Call IV				Put IV			
Ticker	Name	Mean	Std. Dev.	Max	Min	Mean	Std. Dev.	Max	Min	Mean	Std. Dev.	Max	Min
AMBA	Ambarella Inc	45.16	20.44	126.70	6.00	0.51	0.10	1.00	0.30	0.54	0.12	1.01	0.32
AVAV	Aerovironment Inc	33.58	16.74	119.83	17.00	0.43	0.10	0.99	0.23	0.43	0.11	1.07	0.16
BA	Boeing Co	139.18	100.34	440.62	29.36	0.26	0.09	0.85	0.14	0.26	0.10	0.86	0.14
CMTL	Comtech Telecom	30.12	8.70	57.09	9.52	0.39	0.10	1.00	0.17	0.39	0.11	1.37	0.17
CUB	Cubic Corp	43.95	13.26	76.85	18.26	0.37	0.12	1.16	0.11	0.37	0.12	0.97	0.13
ESTL	ELBIT Systems	71.96	37.85	167.70	23.00	0.32	0.08	0.82	0.09	0.36	0.08	1.03	0.14
FET	Forum Energy Tech Inc	17.69	8.82	36.72	0.94	0.51	0.23	2.43	0.17	0.49	0.19	2.39	0.16
FLIR	FLIR Systems Inc	31.65	10.87	63.31	10.82	0.31	0.10	0.87	0.16	0.31	0.11	0.85	0.15
FTI	TechnipFMC plc	32.67	12.85	63.52	10.17	0.38	0.14	1.53	0.16	0.38	0.13	1.17	0.07
GD	General Dynamics	110.93	50.99	229.95	36.31	0.22	0.07	0.73	0.12	0.22	0.07	0.73	0.12
HEI	HEICO Corp	31.36	31.44	145.95	4.57	0.27	0.09	1.69	0.02	0.26	0.07	0.72	0.11
HII	Harris Corp	134.57	75.65	278.57	22.85	0.25	0.05	0.59	0.15	0.25	0.05	0.54	0.15
HRS	Huntington Ingalls Inc.	76.09	47.22	228.98	25.73	0.27	0.10	0.88	0.13	0.27	0.09	0.90	0.12
IRDM	IRIDIUM Com Inc	10.59	5.12	29.90	5.45	0.44	0.10	2.11	0.22	0.45	0.12	2.07	0.22
KTOS	Kratos Inc	12.42	8.40	55.20	2.99	0.55	0.17	2.59	0.25	0.53	0.14	1.93	0.16
LLL	L3 Tech Inc	116.67	52.60	258.80	55.27	0.23	0.07	0.72	0.13	0.23	0.06	0.71	0.12
LMT	Lockheed Martin	164.71	99.16	439.76	58.18	0.21	0.07	0.70	0.09	0.21	0.07	0.75	0.10
MRCY	Mercury Systems Inc	22.15	18.58	88.75	2.55	0.50	0.28	2.76	0.20	0.50	0.28	2.76	0.18
NOC	Northrop Grumman Corp	137.52	100.52	384.87	31.02	0.22	0.07	0.74	0.12	0.21	0.07	0.74	0.08
NVDA	Nvidia Corp	57.49	73.85	289.36	5.90	0.42	0.13	1.27	0.21	0.43	0.13	1.29	0.21
RTN	Raytheon Co	95.61	55.64	232.31	33.57	0.20	0.06	0.62	0.07	0.21	0.06	0.65	0.11
TDG	Teledyne Tech Inc	168.78	137.56	657.93	21.00	0.29	0.11	0.96	0.11	0.29	0.10	0.93	0.03
TDY	Textron Inc	96.89	74.66	386.10	22.05	0.29	0.09	0.08	0.76	0.29	0.10	0.73	0.11
TXT	TransDigm Group	38.28	15.03	73.38	3.75	0.35	0.21	1.74	0.16	0.35	0.21	1.78	0.17

Notes: This table reports the descriptive statistics of the drone companies selected in the paper with respect to their stock price and implied volatility (IV) extracted from both call and put options. The time period is from 02-01-2006 to 31-12-2019, at daily frequency.

Appendix B Additional Results

Table B1: Drone Strikes on Drone Companies ATM Put Implied Volatility: All Strikes

	AMBA	AVAV	BA	CMTL	CUB	ESTL	FET	FLIR	FTI	GD	HEI	HII
Coeff	0.90**	0.78	0.08	1.31**	-0.59	-3.42*	0.13	0.86*	0.23	0.04	6.64***	0.12**
	(0.50)	(0.84)	(0.46)	(0.74)	(1.29)	(2.01)	(1.60)	(0.53)	(0.72)	(0.04)	(2.44)	(0.05)
R^2	5.6	15.2	3.6	15.4	21.9	20.2	22.7	18	11.6	3.7	21.8	8.7
	HRS	**IRDM**	**KTOS**	**LLL**	**LMT**	**MRCY**	**NOC**	**NVDA**	**RTN**	**TDG**	**TDY**	**TXT**
Coeff	0.94*	-0.05	1.94*	0.98**	0.61*	-0.24	-0.11	1.22***	0.06*	1.28*	-1.22	1.41***
	(0.55)	(1.13)	(1.18)	(0.41)	(0.34)	(1.33)	(0.42)	(0.42)	(0.03)	(0.78)	(0.96)	(0.45)
R^2	9.7	20.8	16.2	5.1	5.1	17.5	6.6	9.8	5	3.2	19.1	22.3

Notes: This table presents results of event-study based regressions run through equation 1 where the 24 S&P Kensho Drones Index drone companies ATM Put implied volatility log difference (in percentage) is regressed onto drone strikes dummy variable tracking strikes featuring at least 10 fatalities. We control for the previous lag of the dependent implied volatilities and previous lag of the VIX index. Coefficients, standard error (in parentheses), and R^2 (in percentage) with respect to the drone strikes dummy are reported. Coefficients for controls are omitted to save space. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Period from 02-01-2006 to 31-12-2019, daily frequency.

Table B2: Drone Strikes on Drone Companies ATM Put Implied Volatility: Strikes by Country

	AMBA	AVAV	BA	CMTL	CUB	ESTL	FET	FLIR	FTI	GD	HEI	HII
Afghanistan	1.11**	1.94*	0.05**	2.95***	0.30	NA	0.38	1.40*	0.46	0.06*	-5.26*	1.53**
	(0.61)	(1.14)	(0.03)	(1.09)	(1.80)	NA	(1.91)	(0.97)	(1.07)	(0.04)	(3.09)	(0.68)
Somalia	1.82*	0.91	-0.09	1.30	-0.81	NA	-1.75	-2.08	-1.42	0.01	-8.55*	1.46
	(1.16)	(3.20)	(0.28)	(2.24)	(3.70)	NA	(3.97)	(2.10)	(4.12)	(0.01)	(5.20)	(1.39)
Pakistan	4.53	1.72*	-0.05	1.05	-0.31	4.01*	5.02	-0.04	0.42	0.01	NA	1.20
	(4.14)	(1.04)	(0.08)	(1.53)	(2.54)	(2.24)	(7.66)	(1.44)	(1.18)	(0.08)	NA	2.11
Yemen	0.10	-1.27	0.05	1.16	-5.66*	-4.00	4.79	3.76*	0.37	0.20*	-4.84	-0.70
	(2.22)	(2.48)	(0.12)	(2.34)	(3.36)	(9.25)	(5.61)	(2.19)	(1.94)	(0.12)	(1.26)	1.53
R^2	5.9	15.3	3.7	15.6	22	20.8	22.9	18.1	11.6	3.8	21.6	8.8
	HRS	**IRDM**	**KTOS**	**LLL**	**LMT**	**MRCY**	**NOC**	**NVDA**	**RTN**	**TDG**	**TDY**	**TXT**
Afghanistan	1.44**	1.13	-2.78	1.33**	0.03	-1.92	0.43*	1.62***	0.09*	2.54**	-1.08	1.18**
	(0.77)	(1.49)	(2.00)	(0.58)	(0.05)	(1.81)	(0.29)	(0.58)	(0.05)	(1.11)	(1.31)	(0.64)
Somalia	0.11	0.69	-6.68	0.84	0.04***	0.57	-0.69	2.00*	0.02	5.79**	2.47	2.30*
	(1.58)	(3.05)	(6.97)	(1.22)	(0.01)	(4.91)	(1.22)	(1.20)	(0.11)	(2.29)	(3.56)	(1.31)
Pakistan	0.75	-0.23	-3.67**	1.31*	0.15**	-0.86	-1.61**	0.42	0.04	2.13*	-0.33	0.46
	(1.08)	(2.82)	(2.01)	(0.81)	(0.07)	(2.59)	(0.83)	(0.82)	(0.08)	(1.50)	(1.84)	(0.90)
Yemen	-0.26	-4.66*	0.60	0.78	0.21*	9.92***	1.94*	1.46	-0.06	1.10	7.25***	2.01*
	(1.65)	(2.88)	(3.30)	(1.24)	(0.12)	(3.76)	(1.27)	(1.25)	(0.12)	(2.38)	(2.80)	(1.17)
R^2	9.6	20.9	16.3	5.2	5.2	17.6	6.8	1	5.2	3.6	19.4	22.6

Notes: This table presents results of the event-study based regressions run through equation 2 where the 24 S&P Kensho Drones Index drone companies ATM Put implied volatility log difference (in percentage) is regressed onto drone strikes dummy variable tracking strikes featuring at least 10 fatalities and divided by country target of the strike, namely Afghanistan, Somalia, Pakistan and Yemen. We control for the previous lag of the dependent implied volatilities and previous lag of the VIX index. Coefficients, standard error (in parentheses), and R^2 (in percentage) with respect to the drone strikes dummy are reported. Coefficients for the controls are omitted to save space. NA indicates company implied volatility unavailable. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The period is from 02-01-2006 to 31-12-2019, at daily frequency.

Table B3: Drone Strikes on Drone Companies ATM Put Implied Volatility: Strikes by President

	AMBA	AVAV	BA	CMTL	CUB	ESTL	FET	FLIR	FTI	GD	HEI	HII
Bush	NA	0.60	0.59	3.76*	-4.58	8.44**	NA	0.33	4.17**	0.26*	NA	NA
	NA	(3.49)	(1.63)	(2.26)	(4.90)	(3.65)	NA	(2.78)	(2.28)	(0.15)	NA	NA
Obama	0.80*	1.01	-0.06	2.32**	-0.99	1.70	1.08	1.63*	-0.16	0.08*	5.96*	1.13*
	(0.51)	(1.02)	(0.52)	(0.99)	(1.63)	(2.70)	(2.10)	(0.92)	(0.76)	(0.05)	(3.77)	(0.70)
Trump	1.04*	0.45	1.04	0.79	0.36	NA	1.90	1.29	NA	-0.04	-8.04**	1.18
	(0.65)	(1.60)	(1.20)	(1.35)	(2.24)	NA	(2.38)	(1.27)	NA	(0.07)	(3.31)	(0.85)
R^2	5.6	15.3	3.6	15.5	22	21	22.8	18	11.7	3.3	21.7	8.7
	HRS	IRDM	KTOS	LLL	LMT	MRCY	NOC	NVDA	RTN	TDG	TDY	TXT
Bush	3.30*	NA	0.09	3.19**	0.33***	-2.51	2.46*	4.75***	0.34**	-0.55	0.21	3.49***
	(2.09)	NA	(3.87)	(1.58)	(0.15)	(4.91)	(1.41)	(1.59)	(0.15)	(3.29)	(3.55)	(1.63)
Obama	0.52	-0.33	2.12*	0.73*	0.06	-0.03	-0.54	1.16**	0.05	0.22	-2.24**	1.44***
	(0.69)	(1.40)	(1.36)	(0.42)	(0.05)	(1.65)	(0.53)	(0.53)	(0.05)	(1.01)	(1.18)	(0.57)
Trump	1.19	1.02	NA	1.09*	-0.01	0.27	0.08	1.49**	-0.06	3.63***	1.15	0.81
	(0.96)	(1.85)	NA	(0.73)	(0.07)	(2.52)	(0.74)	(0.73)	(0.07)	(1.39)	(1.80)	(0.79)
R^2	9.6	20.8	16.2	5.1	5.2	17.4	6.7	11.9	5.2	3.3	19.2	2.3

Notes: This table presents results of event-study based regressions run through equation 3 where the 24 S&P Kensho Drones Index drone companies ATM Put implied volatility log difference (in percentage) is regressed onto drone strikes dummy variable tracking strikes featuring at least 10 fatalities and divided by US president in office at the time of the strike, namely Bush, Obama and Trump. We control for the previous lag of the dependent implied volatilities and previous lag of the VIX index. Coefficients, standard error (in parentheses), and R^2 (in percentage) with respect to the drone strikes dummy are reported. Coefficients for the controls are omitted to save space. NA indicates company implied volatility unavailable. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The period is from 02-01-2006 to 31-12-2019, at daily frequency.

Table B4: Drone Strikes and Fama-French Factors on Drone Companies Implied Volatility: All Strikes

	AMBA	AVAV	BA	CMTL	CUB	ESTL	FET	FLIR	FTI	GD	HEI	HII
Drone	1.44***	1.00	1.21**	1.55**	1.57	-1.17	0.04*	1.43**	1.48***	1.18***	0.20	1.69***
	(0.52)	(0.83)	(0.51)	(0.74)	(1.44)	(2.18)	(0.02)	(0.59)	(0.54)	(0.43)	(0.28)	(0.58)
Adj. R^2	3.9	14.9	3.1	12.4	24.9	17.4	17.2	11.4	6.9	2.6	18.7	7.4
	HRS	IRDM	KTOS	LLL	LMT	MRCY	NOC	NVDA	RTN	TDG	TDY	TXT
Drone	0.09*	3.52***	0.46	1.52***	1.01**	1.46	0.84*	1.64***	1.00**	1.95***	1.11	1.57***
	(0.05)	(0.94)	(1.38)	(0.46)	(0.46)	(1.28)	(0.46)	(0.46)	(0.45)	(0.73)	(1.06)	(0.49)
Adj. R^2	7.4	21.9	12.7	5.3	5.5	18.5	2.5	1.7	3.5	6.9	22.0	1.2

Notes: This table presents results of event-study based regressions run through equation 1 where the 24 S&P Kensho Drones Index drone companies implied volatility log difference (in percentage) is regressed onto drone strikes dummy variable tracking strikes featuring at least 10 fatalities. We control for the previous lag of the dependent implied volatilities, previous lag of the VIX index and also the Fama-French five factors, namely ER, HML, SMB, RMW, and CMA. Coefficients, standard error (in parentheses), and adjusted R^2 (in percentage) with respect to the drone strikes dummy are reported. Coefficients for controls are omitted to save space. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The period is from 02-01-2006 to 31-12-2019, at daily frequency.

Table B5: Drone Strikes and Fama-French Factors on Drone Companies Implied Volatility: Strikes by Country

	AMBA	AVAV	BA	CMTL	CUB	ESTL	FET	FLIR	FTI	GD	HEI	HII
Afghanistan	1.88***	1.85*	1.80***	1.59*	2.65	NA	2.42	1.67*	2.46***	1.97***	2.33	0.24***
	(0.62)	(1.10)	(0.68)	(0.96)	(2.01)	NA	(2.18)	(0.95)	(0.84)	(0.62)	(3.45)	(0.08)
Somalia	0.48	0.29	-5.01*	2.66	-3.49	NA	6.08	-1.82	-3.21	0.22	-5.29	0.20
	(1.23)	(3.01)	(3.07)	(2.15)	(4.11)	NA	(4.51)	(1.93)	(3.35)	(1.27)	(6.33)	(0.15)
Pakistan	-1.25	-0.83	-1.62**	1.02	-0.14	-1.63	1.43*	1.11	-2.26**	0.16	NA	0.01
	(4.16)	(1.59)	(0.88)	(1.46)	(0.27)	(2.22)	(0.85)	(1.34)	(0.98)	(0.87)	NA	(0.23)
Yemen	1.01	2.79	2.60*	0.61	9.36**	4.81	4.33	5.24***	1.23	1.55	-2.13*	-0.10
	(2.22)	(2.23)	(1.37)	(2.22)	(4.29)	(9.22)	(6.36)	(2.03)	(1.61)	(1.43)	(1.13)	(0.16)
Adj. R^2	3.8	14.8	3.1	12.2	24.8	17.6	17.2	11.6	7.0	2.5	18.7	7.8
	HRS	IRDM	KTOS	LLL	LMT	MRCY	NOC	NVDA	RTN	TDG	TDY	TXT
Afghanistan	0.07	4.10***	0.92	1.94***	1.12**	0.62	0.80	2.12***	1.39**	2.19**	-0.41	1.52**
	(0.08)	(1.27)	(2.15)	(0.66)	(0.61)	(1.75)	(0.65)	(0.66)	(0.63)	(1.00)	(1.44)	(0.67)
Somalia	0.05	4.36*	0.44	2.64**	0.49	1.87	2.22*	0.79	0.42	1.01	2.81	2.42*
	(0.17)	(2.56)	(7.47)	(1.38)	(1.29)	(4.72)	(1.33)	(1.32)	(1.25)	(2.04)	(3.88)	(1.37)
Pakistan	0.19	-1.59	3.32*	0.36	1.77**	-0.02	0.82	1.32*	-0.11	1.82*	1.25	0.46
	(0.14)	(2.37)	(1.93)	(0.93)	(0.89)	(2.44)	(0.92)	(0.90)	(0.88)	(1.11)	(2.01)	(0.95)
Yemen	0.37**	5.35**	-3.52	0.85	1.25	6.16*	1.98	1.99*	2.77**	2.34	6.48**	2.65*
	(0.17)	(2.64)	(3.53)	(1.41)	(1.35)	(3.75)	(1.38)	(1.13)	(1.33)	(2.14)	(3.03)	(1.45)
Adj. R^2	7.4	22.2	13.1	5.2	5.3	18.6	2.4	1.7	3.5	6.7	22.2	1.2

Notes: This table presents results of the event-study based regressions run through equation 2 where the 24 S&P Kensho Drones Index drone companies implied volatility log difference (in percentage) is regressed onto drone strikes dummy variable tracking strikes featuring at least 10 fatalities and divided by target country of the strike, namely Afghanistan, Somalia, Pakistan and Yemen. We control for the previous lag of the dependent implied volatilities, previous lag of the VIX index and also the Fama-French five factors, namely ER, HML, SMB, RMW, and CMA. Coefficients, standard error (in parentheses), and adjusted R^2 (in percentage) with respect to the drone strikes dummy are reported. Coefficients for the controls are omitted to save space. NA indicates company implied volatility unavailable. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The period is from 02-01-2006 to 31-12-2019, at daily frequency.

Table B6: Drone Strikes and Fama-French Factors on Drone Companies Implied Volatility: Strikes by President

	AMBA	AVAV	BA	CMTL	CUB	ESTL	FET	FLIR	FTI	GD	HEI	HII
Bush	NA	6.97**	3.11*	5.06*	7.55*	0.53	NA	3.46	0.71***	3.18**	NA	NA
	NA	(3.38)	(1.77)	(2.84)	(4.23)	(3.64)	NA	(2.57)	(0.18)	(1.68)	NA	NA
Obama	1.74***	0.97	1.15**	1.59*	2.34	-2.21	2.91	1.61*	0.09*	1.31***	4.61	1.65**
	(0.72)	(0.99)	(0.47)	(0.93)	(1.82)	(2.70)	(2.39)	(0.86)	(0.05)	(0.55)	(4.51)	(0.74)
Trump	1.12*	1.04	0.83	0.68	-1.02	NA	4.00*	0.45	NA	0.42	1.52	1.51*
	(0.64)	(1.15)	(1.32)	(1.30)	(2.46)	NA	(2.53)	(1.12)	NA	(0.76)	(3.71)	(0.88)
Adj. R^2	3.8	14.9	2.9	12.6	24.8	17.4	17.2	11.4	7.2	2.6	18.6	7.2

	HRS	IRDM	KTOS	LLL	LMT	MRCY	NOC	NVDA	RTN	TDG	TDY	TXT
Bush	0.37*	NA	3.14	4.83***	5.09***	-0.31	4.21**	5.89***	3.43**	6.52**	2.64	4.17**
	(0.22)	NA	(4.15)	(1.70)	(1.70)	(0.47)	(1.74)	(1.73)	(1.69)	(2.95)	(3.88)	(1.84)
Obama	0.13*	4.15***	0.20	1.70***	1.18**	0.19	1.04*	1.42**	1.23**	2.18***	1.53	1.91***
	(0.07)	(1.11)	(1.47)	(0.59)	(0.57)	(0.15)	(0.55)	(0.57)	(0.56)	(0.90)	(1.29)	(0.61)
Trump	0.07	2.81*	NA	0.32	-0.14	0.12	-0.32	2.05***	-0.08	0.54	0.23	0.47
	(0.10)	(1.57)	NA	(0.83)	(0.77)	(0.24)	(0.82)	(0.79)	(0.77)	(1.24)	(1.97)	(0.83)
Adj. R^2	7.4	21.8	12.6	5.4	5.5	18.3	2.4	1.8	3.4	6.8	22.0	1.5

Notes: This table presents results of the event-study based regression run through equation 3 where the 24 S&P Kensho Drones Index drone companies implied volatility log difference (in percentage) is regressed onto drone strikes dummy variable tracking strikes featuring at least 10 fatalities and divided by US president in office at the time of the strike, namely Bush, Obama and Trump. We control for the previous lag of the dependent implied volatilities, previous lag of the VIX index and also the Fama-French five factors, namely ER, HML, SMB, RMW, and CMA. Coefficients, standard error (in parentheses), and adjusted R^2 (in percentage) with respect to the drone strikes dummy are reported. Coefficients for the controls are omitted to save space. NA indicates company implied volatility unavailable. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The period is from 02-01-2006 to 31-12-2019, at daily frequency.

Table B7: Drone Strikes and Fama-French Factors on Drone Companies Prices: All Strikes

	AVAV	AMBA	BA	CMTL	CUB	ESTL	FLIR	FET	GD	HEI	HRS	HII
Coeff	0.05**	-0.13	-0.27**	0.05	-0.30*	-0.23*	-0.31**	-0.47*	-0.01*	0.03**	0.01	-0.05
	(0.02)	(0.30)	(0.12)	(0.19)	(0.18)	(0.12)	(0.14)	(0.27)	(0.01)	(0.01)	(0.15)	(0.13)
Adj. R^2	0.3	0.2	0.4	0.4	0.7	1.3	0.6	1.3	0.2	0.6	15.2	0.3

	IRDM	KTOS	LLL	LMT	MRCY	NOC	NVDA	RTN	FTI	TDY	TXT	TDG
Coeff	-0.47***	0.7**	0.01	-0.09	0.42**	0.01	-0.39**	0.01	-0.54***	-0.19	-0.03	-0.33**
	(0.17)	(0.25)	(0.14)	(0.08)	(0.23)	(0.11)	(0.22)	(0.11)	(0.19)	(0.14)	(0.20)	(0.14)
Adj. R^2	0.5	0.5	0.2	0.7	0.9	0.4	0.3	0.1	0.7	1.1	0.2	0.2

Notes: This table presents results of event-study based regressions run through equation 4 where the 24 S&P Kensho Drones Index drone companies price log returns (in percentage) is regressed onto drone strikes dummy variable tracking strikes featuring at least 10 fatalities. We control for the previous lag of the dependent stock prices, previous lag of the VIX index and also the Fama-French five factors, namely ER, HML, SMB, RMW, and CMA. Coefficients, standard error (in parentheses), and adjusted R^2 (in percentage) with respect to the drone strikes dummy are reported. Coefficients for controls are omitted to save space. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The period is from 02-01-2006 to 31-12-2019, at daily frequency.

Table B8: Drone Strikes and Fama-French Factors on Drone Companies Prices: Strikes by Country

	AVAV	AMBA	BA	CMTL	CUB	ESTL	FLIR	FET	GD	HEI	HRS	HII
Afghanistan	0.45*	0.02	0.03*	0.09	-0.21	0.04	0.02	-0.21	-0.04	-0.05	-0.34*	-0.01
	(0.27)	(0.35)	(0.18)	(0.26)	(0.24)	(0.18)	(0.22)	(0.34)	(0.15)	(0.23)	(0.18)	(0.17)
Somalia	0.14	0.06	0.05	-0.04	-0.38	0.10**	-0.01	-1.11*	0.08	0.21	0.29	-0.24
	(0.58)	(0.70)	(0.04)	(0.54)	(0.49)	(0.04)	(0.43)	(0.62)	(0.30)	(0.47)	(0.38)	(0.34)
Pakistan	0.62	-1.22	-0.05**	-0.07	0.47	-0.06**	-0.61**	-0.69	-0.31	-0.51*	-0.15	-0.27
	(0.42)	(2.30)	(0.02)	(0.38)	(0.34)	(0.02)	(0.29)	(1.31)	(0.21)	(0.31)	(0.26)	(0.49)
Yemen	-0.41	-1.79	-0.05	-0.05	-0.47	-0.06	-0.99**	-1.98**	-0.69**	0.10	-0.14	-0.12
	(0.59)	(1.23)	(0.03)	(0.05)	(0.51)	(0.04)	(0.44)	(0.93)	(0.32)	(0.46)	(0.39)	(0.36)
Adj. R^2	0.2	0.2	0.3	0.3	0.6	1.5	0.6	1.2	0.4	0.5	1.6	0.6

	IRDM	KTOS	LLL	LMT	MRCY	NOC	NVDA	RTN	FTI	TDY	TXT	TDG
Afghanistan	-0.05**	-0.55*	0.02	0.05	-0.51	0.11	-0.26	0.01	-0.39*	-0.05	0.08	-0.39**
	(0.02)	(0.33)	(0.15)	(0.13)	(0.33)	(0.15)	(0.31)	(0.14)	(0.23)	(0.19)	(0.28)	(0.19)
Somalia	0.09*	-0.18	0.48*	0.11	0.22	-0.17	0.21	-0.02	-0.14	-0.21	-0.01	0.52
	(0.05)	(0.69)	(0.30)	(0.28)	(0.67)	(0.31)	(0.63)	(0.03)	(0.54)	(0.39)	(0.06)	(0.41)
Pakistan	0.03	0.71	-0.03	-0.46**	0.44	0.09	-0.02	0.08	-0.69**	-0.25	0.03	-0.26
	(0.04)	(0.48)	(0.21)	(0.19)	(0.46)	(0.21)	(0.41)	(0.19)	(0.36)	(0.27)	(0.04)	(0.28)
Yemen	-0.02	-2.69*	-0.41	-0.27	-1.57**	-0.52*	-0.47	-0.03	-1.56***	-0.35	-0.08	-0.49
	(0.06)	(1.54)	(0.31)	(0.29)	(0.72)	(0.31)	(0.64)	(0.02)	(0.54)	(0.40)	(0.06)	(0.42)
Adj. R^2	0.3	0.3	0.2	0.8	0.9	0.1	0.1	0.2	0.8	1.2	0.2	0.3

Notes: This table presents results of the event-study based regressions run through equation 5 where the 24 S&P Kensho Drones Index drone companies price log returns (in percentage) is regressed onto drone strikes dummy variable tracking strikes featuring at least 10 fatalities and divided by target country of the strike, namely Afghanistan, Somalia, Pakistan and Yemen. We control for the previous lag of the dependent stock prices, previous lag of the VIX index and also the Fama-French five factors, namely ER, HML, SMB, RMW, and CMA. Coefficients, standard error (in parentheses), and adjusted R^2 (in percentage) with respect to the drone strikes dummy are reported. Coefficients for the controls are omitted to save space. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The period is from 02-01-2006 to 31-12-2019, at daily frequency.

Table B9: Drone Strikes and Fama-French Factors on Drone Companies Prices: Strikes by President

	AVAV	AMBA	BA	CMTL	CUB	ESTL	FLIR	FET	GD	HEI	HRS	HII
Bush	-0.24***	NA	-0.13***	-0.13*	-1.11*	-0.17***	-1.52***	NA	-1.39***	-1.33**	1.64***	NA
	(0.08)	NA	(0.05)	(0.07)	(0.64)	(0.05)	(0.57)	NA	(0.39)	(0.61)	(0.51)	NA
Obama	0.02	-0.50	-0.02*	-0.01	-0.01	-0.01	-0.14	-0.51*	-0.14	0.08	0.41**	-0.12
	(0.02)	(0.40)	(0.01)	(0.02)	(0.21)	(0.02)	(0.19)	(0.33)	(0.13)	(0.21)	(0.17)	(0.17)
Trump	0.05*	0.17	0.02**	0.05*	-0.15	0.02	-0.05	-0.55	0.05	0.21	0.36*	0.03
	(0.03)	(0.42)	(0.01)	(0.03)	(0.29)	(0.02)	(0.24)	(0.35)	(0.18)	(0.27)	(0.22)	(0.19)
Adj. R^2	0.6	0.1	0.4	0.4	0.6	1.7	0.8	1.1	0.6	0.8	1.6	0.2

	IRDM	KTOS	LLL	LMT	MRCY	NOC	NVDA	RTN	FTI	TDY	TXT	TDG
Bush	-0.07	0.19	-0.95**	-1.54***	-0.02	-0.67*	-0.85	-0.68*	-3.30***	-1.73***	-1.71**	-2.16***
	(0.08)	(0.90)	(0.39)	(0.37)	(0.08)	(0.39)	(0.84)	(0.36)	(0.69)	(0.51)	(0.77)	(0.54)
Obama	-0.01	0.11	-0.04	-0.04	0.02	0.03	-0.37*	0.06	-0.38*	-0.04	0.16	-0.22
	(0.02)	(0.31)	(0.13)	(0.13)	(0.03)	(0.13)	(0.22)	(0.13)	(0.23)	(0.18)	(0.26)	(0.17)
Trump	0.08**	1.22***	0.29	0.12	0.01	0.09	0.22	0.02	-0.46*	-0.04	-0.07	-0.07
	(0.04)	(0.41)	(0.18)	(0.16)	(0.04)	(0.20)	(0.35)	(0.18)	(0.31)	(0.24)	(0.35)	(0.24)
Adj. R^2	0.4	0.3	0.4	1.1	0.8	0.1	0.2	0.3	1.1	1.6	0.2	0.5

Notes: This table presents results of event-study based regressions run through equation 6 where the 24 S&P Kensho Drones Index drone companies price log returns (in percentage) is regressed onto drone strikes dummy variable tracking strikes featuring at least 10 fatalities and divided by US president in office at the time of the strike, namely Bush, Obama and Trump. We control for the previous lag of the dependent stock prices, previous lag of the VIX index and also the Fama-French five factors, namely ER, HML, SMB, RMW, and CMA. Coefficients, standard error (in parentheses), and adjusted R^2 (in percentage) with respect to the drone strikes dummy are reported. Coefficients for the controls are omitted to save space. NA indicates company implied volatility unavailable. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The period is from 02-01-2006 to 31-12-2019, at daily frequency.