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Economic uncertainty, oil prices, hedging and U.S. stock returns of the airline industry☆

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ABSTRACT

This paper examines the impacts of economic policy uncertainty and oil price shocks on stock returns of U.S. airlines using both industry and firm-level data. Our empirical approach considers a structural vector-autoregressive model with variables recognized to be important for airline returns including jet fuel price volatility. Empirical results confirm that oil price increase, economic uncertainty and jet fuel price volatility have significantly adverse effect on real stock returns of airlines both at industry and at firm level. In addition, we also find that hedging future fuel purchase has statistically positive impact on the smaller airlines. Our results suggest policy implications for practitioners, managers of airline industry and commodity investors.

1. Introduction

Airline industry is exposed to substantial risks. One relevant risk for airline industry is their exposure to jet fuel price fluctuations representing one of the major costs. Using U.S. data over the period 1992–2003, Carter et al. (2006) realize jet fuel bill represents about 13.6% of operating costs. Jet fuel costs faced by the airline industry have experienced great volatility during recent years. For example, jet fuel costs account for around 32.3% of operating expenses in 2012 ($111.8 per barrel of Brent crude oil) and 17% of total operating expenses in 2017 ($54.4 per barrel of Brent crude oil) (International Air Transport Association, 2017). The new era of lower crude oil prices and lower jet fuel prices have translated to lower operating expenses and higher net profits of airline industry (International Air Transport Association, 2016; U.S. Energy Information Administration, 2017).

Furthermore, the airline industry is also exposed to additional risks such as market demand, financial (i.e., interest rates and exchange rates fluctuations), global events such as terrorists attack and government regulations. Airline industry is facing different risks and uncertainty. Previous studies show that uncertainty shocks significantly influence firms' investment and labor hiring decisions (see Bloom et al., 2007; Bloom, 2009). Kang et al. (2014) find that economic uncertainty weakening firm-level investment is related to the business cycle. Baker et al. (2016) recently show that policy-related economic uncertainty raises stock price volatility,

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reduces investment and lowers employment of sectors sensitive to economic policies.[1]

Following previous related literature on the nexus between oil prices and stock market returns (for example, Jones & Kaul, 1996; Park & Ratti, 2008; Cunado & Perez de Gracia, 2014) and the idea that responses of stock returns are different to oil price shocks across different industries (e.g., Elyasiani et al., 2011; Narayan & Sharma, 2011), this paper specifically analyzes the nexus between oil prices and stock returns of airline industry.[2] Some related papers investigate the nexus between oil prices and transport (automobile or airline) firms. Hammoudeh and Li (2005) obtain that oil price shocks adversely affect the U.S. transportation industry. Using international dataset, Nandha and Brooks (2009) show that the fluctuation of oil prices plays an important role in explaining the stock returns of transport industry. Aggarwal et al. (2012) present that oil price shocks asymmetrically affect the stock returns of transportation firms. Elyasiani et al. (2011) find that oil price changes adversely affect the U.S. air transport sector. In a different approach, using firm return level data, Narayan and Sharma (2011) find that oil price changes are positively associated with the stock returns of transportation sector. Mohanty et al. (2014) analyze the nexus between oil prices and real stock returns of the U.S. travel and leisure industry. The authors present that the exposures of oil prices are significantly negative for airlines during 1983–2011. Kristjanpoller and Concha (2016) analyze the effect of changes in jet fuel and oil prices on the equity returns of airline companies. Using Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models, they find that increases in crude oil and fuel price cause increases in airline stock prices. In a recent paper, Yun and Yoon (2019) investigate the effect of oil price shocks on the stock returns and volatility of four major Asian airlines. The authors obtain that the volatility spillover effect is relatively stronger than the return spillover effect between oil and major airline stock prices.[3]

To investigate whether oil price shocks matters for real stock returns of U.S. airline industry with policy-related economic uncertainty, we take two complementary approaches. We first analyze the importance of crude oil prices on the stock prices of U.S. airline industry using a Structural Vector-Autoregressive (SVAR) model over the period from 1985 to 2017. The empirical analyses not only take into account crude oil prices but also two relevant explanatory variables such as volatility of jet fuel prices and policy-related economic uncertainty. Using aggregate-level data in SVAR analyses potentially captures transmission channels through which oil price innovations and policy-related economic uncertainty affects the stock prices of airline industry on average. The economic implications are potentially interesting for policy makers and investment portfolio managers but not explicitly identifying the causal effect on specific companies. Second, we provide new empirical evidence at firm-level daily data of real stock returns of major U.S. airline companies (i.e., Delta, Southwest, American, United Continental, Alaska, Skywest, Allegiant, and Hawaiian Airlines). We additionally investigate how jet fuel hedging activity affects the major airline stock returns at firm-level, as Carter et al. (2006) show that hedging future fuel purchase has significant positive impact on airline firm values.[4] The analyses conducted at firm-level data provide corroborative evidence to that at aggregate-level data and help further understanding different economic/policy implications and identifying specific risk management strategies for individual airline companies.

The main empirical findings obtained in the paper are the following. First, the industry-level (and firm-level) evidence suggest that oil price dynamics and policy uncertainty innovations cause volatility of jet fuel prices to rise. Second, jet fuel volatility interplays with crude oil price shocks and policy-related economic uncertainty, which in turn significantly accounts for the overall variation in the real airline stock return. Third, results suggest that oil price increases (and, also, the volatility of jet fuel prices) cause a decreased airline stock return. Finally, the results confirm that hedging future fuel purchase has an effect on real airline stock returns.

Our study contributes to previous related literature in four directions. First, the paper is specially focused on the stock returns of airline industry. Airline industry is highly exposure to both jet fuel and crude oil price dynamics.[5] Second, we are estimating the connection between crude oil price innovations and airlineś stock returns at both the industry/macro aggregate level and firm/micro level.[6] Third, this paper also contributes to the literature by analyzing the nexus of policy-related economic uncertainty and firm-level stock returns of airline industry.[7] Finally, following the idea that hedging affect firm value (Carter et al., 2006), we analyze whether hedging future fuel purchase explain airline firm value. In summary, the major contribution of our study is to investigate the response of real airline corporate stock returns to policy-related economic uncertainty, oil prices and the volatility of jet fuel prices at both macro and firm levels.

The paper is structured as follows. Section 2 uses a SVAR to show the dynamics of real stock return responses to policy-related economic uncertainty and the oil price innovations at aggregate industry-level data. Section 3 covers the firm-level analysis which

[1] For example, Degiannakis, Filis, and Arora (2018) show that oil price changes are associated with the economic uncertainty.

[2] A recent review by Degiannakis, Filis, and Panagiotakopoulou (2018) covers the nexus between oil price fluctuations and stock market movement.

[3] In a recent paper, Pal and Mitra (2019) examine the co-movement between stock returns of automobile industry and the crude oil prices.

[4] Carter et al. (2006) show that airlines also use avenues such as fuel pass-through and chartering to manage fuel price risk, which is not the same as the future fuel purchase hedging. Lin and Chang (2009) find that the hedging on jet fuel prices has positive value on airline companies.

[5] It has been observed that crude oil fluctuations are related to jet fuel fluctuations (U.S. Energy Information Administration, 2017) and Kristjanpoller and Concha (2016) investigate the effect of both price of oil and jet fuel price on airline stock returns. Using international dataset, Park and Ratti (2008) shows that the volatility of crude oil price lowers real stock returns.

[6] Previous empirical literature on crude oil prices and stock returns of different industries is Giovannini et al. (2006), Boyer and Filion (2007), Sadorsky (2008), Narayan and Sharma (2011), Mohanty et al. (2013), Tsai (2015), Diaz and Perez de Gracia (2017) and Kang et al. (2017). Further studies document that oil prices affect not only the aggregate stock market returns but also the stock returns in the firm level (Narayan and Sharma, 2011; Lee et al., 2011).

[7] Using firm-level data, Baker et al. (2016) find that policy-related economic uncertainty causes higher stock volatility, lower firm-level investment, and greater unemployment.

allows us to investigate the impact of both crude oil prices, volatility of jet fuel prices and policy-related economic uncertainty on the real returns of major U.S. airline firms using daily data. Section 4 includes alternative oil price measures and the impact of COVID-19 on the airline industry. Finally, Section 5 presents the main conclusions.

2. Dynamics of oil price shocks, policy-related economic uncertainty, and the stock return of airline industry

We analyze the role of the price of oil on real stock returns of U.S. airline industry using a SVAR model in this section, which takes into account crude oil prices as well as two relevant explanatory variables such as volatility of jet fuel prices and economic policy uncertainty. We believe that our empirical analysis is the first work that potentially capture the transmission channels through which oil price innovations and policy-related economic uncertainty affects the real stock returns of airline industry at aggregate-level data on average. The economic implications are potentially interesting for policy makers and investment portfolio managers who are particularly focused on the airline industry.

2.1. Data source

Our monthly data is from 1985 M1 to 2017 M12 including the index of U.S. policy-related economic uncertainty developed by Baker et al. (2016). The index shows a summary of broad news-based policy-related economic uncertainty, forecasters' disagreement interquartile range on the inflation and government spending, and the taxation code set to expire in the future.[8] We define the real oil price as the U.S. refiners' acquisition cost of imported crude oil divided by the seasonally adjusted Consumer Price Index (CPI). The jet fuel price volatility is the standard deviation of 24-month rolling samples by using the prices of U.S. refiners' kerosene-type jet fuel sales to end consumers.[9] We obtain both prices from the Department of Energy. The short-term 3-month T-Bill interest rate, the seasonally adjusted industrial production index and the seasonally adjusted CPI of all items are drawn from the Federal Reserve Economic Data (FRED) of Federal Reserve Bank in St. Louis.[10] The real stock return of airline industry (Standard Industrial Classification (SIC) 4512 airline transportations scheduled) is calculated using the value weighted stock returns adjusted by the CPI. As a robustness check, we use real stock returns of major U.S. airline firms (Delta Air Lines (DAL), Southwest Airlines (LUV), United Airlines (UAL), American Airlines (AAL)). The data in the stock market is drawn from the Compustat Merged Database/Center for Research in Security Prices (CRSP).[11]

We present the time series of the global real oil prices, jet fuel price volatility, policy-related economic uncertainty, and the real airline industry stock returns over 1985 M1- 2017 M12. As observed, the rises in the policy-related economic uncertainty are used to be followed by a movement of oil/jet fuel prices and real returns of airline industrial stocks, for example, during the periods of Terrorists Attack in 2001, Global Financial Crisis over 2008–2009, and the slow oil market between 2014 and 2015. The volatility of jet fuel prices appears to lag the movement of global oil prices by at least one month and is relatively smaller.

2.2. Methodology

The SVAR includes similar variables proposed by Park and Ratti (2008) and Galí and Gambetti (2015) and additional variables of our interest such as oil/jet fuel prices and policy-related economic uncertainty to investigate whether their shocks have significantly impact effects on the real stock returns of airline companies. Kang and Ratti (2013) show that innovations in the policy-related economic uncertainty raise the impulse responses of real stock market returns to oil price shocks. Specifically, our SVAR model of order p is specified as

$$A_0 y_t = c_0 + \sum_{i=1}^{p} A_i y_{t-i} + \varepsilon_t \tag{1}$$

where the vector $y_t = (\Delta ip_t, \Delta cpi_t, rpo_t, jfv_t, int_t, pu_t, ret_t)$ includes seven endogenous variables: Δip_t the percentage change in the industrial production, Δcpi_t the percentage change in the CPI, rpo_t the real oil price, jfv_t the jet fuel price volatility, int_t the short-term interest rate, pu_t the policy-related economic uncertainty index, and ret_t the real airline stock return.[12] A_0 and A_i denotes 7×7 coefficient matrices. The vectors c_0 and ε_t refer to the constant coefficients and the structural disturbances of error terms respectively.

[8] The index and its construction are available at http://www.policyuncertainty.com.

[9] Blanchard and Simon (2001) show the volatility of U.S. GDP using a rolling standard deviation and find that the measure is robust to other calculations using series with different frequencies and alternative statistics methods. When we use the daily spot jet fuel prices to generate monthly standard deviation, the impulse response functions are similar but relatively less statistically significant, likely because of the noise issues using the daily prices.

[10] The macroeconomic data series is available at https://fred.stlouisfed.org/.

[11] Note that the macroeconomic data obtained are seasonally adjusted time-series. Real stock returns are nominal stock returns divided by the U.S. seasonally adjusted CPI. The avenues on the future research would explore the effects of oil shocks in a low/high season and how the effects driven by the weekly/seasonal patterns of travels.

[12] We acknowledge that the study of the dynamics of crude oil/jet fuel prices in levels, their volatility and the stock market returns may use the GARCH-in-Mean VAR in Elder and Serletis (2010). It would simplify the specification and excludes the measure of volatility censored at zero in the VAR model. Alternatively, the stochastic volatility specification proposed by Jo (2014) is able to separately identify the effect of first-moment and second-moment shocks.

In the dynamic analysis, we take the lag length $p = 12$ in order to capture the possible delayed effects of oil price shocks on the economy and mitigate the potential serial correlation in the time-series model (e.g., Sims, 1998; Sims, Stock, & Watson, 1990; Hamilton & Herrera, 2004; Hamilton, 2008; Kilian, 2009; Kilian & Park, 2009). The preliminary tests are conducted by Augmented Dickey-Fuller (ADF), Phillips-Perron (PP) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) for the time-series stationarity of the seven endogenous variables in Model (1). The test shows that the time-series of Δip_t, Δcpi_t, pu_t, ret_t are stationary, whereas the variables of rpo_t, jfv_t, int_t contain a unit root at the 5% significant level. As our model is reasonably consistently estimated with long lags of 12-month in the model, we follow the literature (Kilian, 2009; Kilian & Park, 2009; Gospodinov et al., 2013; Kilian & Murphy, 2014) to use the variables rpo_t, jfv_t, and int_t in levels in the main analysis.

The restriction identification of shocks to oil price/jet fuel volatility shocks and innovations in policy-related economic uncertainty is motivated by the Park and Ratti (2008) and Galí and Gambetti (2015). We assume that real airline stock returns instantaneously respond to each structural shock by using Cholesky decomposition to orthogonalize the residuals in Model (1).[13] As observed in Fig. 1 movement in the volatility of jet fuel prices lag changes in the real oil prices, which indicator is implicitly weighted toward the effects of different sources of uncertainty on the jet fuel prices. It is assumed that innovations in the volatility of jet fuel prices lag the movement of global real oil prices by more than one month,[14] in the sense that domestic jet fuel oil market innovations do not affect the imported crude oil prices within a month. Adams and Gerner (2012) show that a barrel of crude oil converts 13% into jet fuel oil in the refining process. U.S. refiners are generally crude oil price takers in the international oil market and are retail jet fuel price makers for domestic users (Kilian, 2010). However, shocks to both oil and jet fuel prices are assumed to respond immediately to own shocks and have simultaneous effects on the real variables of policy-related economic uncertainty and the real airline stock return. In line with Pastor and Veronesi (2012) who document that policy uncertainty lowers stock prices, we have the real airline stock returns variable ordered last. It is consistent with the traditional view on oil prices predetermined to the real economy by Lee et al. (1995) and Kilian and Park (2009) for example. Finally, we order other endogenous variables Δip_t, Δcpi_t, and int_t following Christiano et al. (2005) and Galí and Gambetti (2015) who assume that innovations in the monetary policy does not affect the real output and not respond to innovations in the stock market within a month. We additionally include the price level in the model, as Walsh (2017) argues that a funds rate shock causing increases in the price level that are the result of an absence of inflation-sensitive prices in the SVAR system.[15]

2.3. SVAR estimates

We first normalize the structural shocks and consistently estimate the reduced-form VAR model by the least-squares, used to recover the SVAR Model (1). Second, we follow Gonçalves and Kilian (2004) to use recursive-design wild bootstrap with 2,000 replications to generate the impulse response functions in twenty-four months and their one-standard error bands to one-standard deviation structural innovations.

2.3.1. Nexus of real oil price, jet fuel volatility, and the policy-related economic uncertainty

In Column 3 of Fig. 2, an unanticipated rise in real oil prices causes increases in the volatility of jet fuel prices that persists over the forecasting horizons 24 months. Unexpected shocks to real oil prices cause statistically significantly negative (positive) effects on the policy-related economic uncertainty in the 1st and 2nd months (9th, 14th, 19th and 24th months). It implies that oil price increases cause significant movement in the economic policy uncertainty which rises on average and in the long run in particular. In Column 4 of Fig. 2, unexpected shocks to jet fuel price volatility lowers the real oil prices over the next 8–14 months. Unanticipated shocks to jet fuel price volatility significantly positively impact the policy-related economic uncertainty in a window between the 5th and 24th month. In Column 6 of Fig. 2, a rise in the policy uncertainty causes increases in the volatility of jet fuel prices over 1–14 months and a drop afterward. Additionally, in 60 months as Panel A in Table 1 shows, 38.9% and 11.3% of the overall variation in the jet fuel price volatility is explained by shocks to crude oil prices and policy-related economic uncertainty respectively.

In summary, oil price shocks are positively related to statistically significantly immediate and persistent increases in the jet fuel volatility when policy-related economic uncertainty heightens in two months. Innovations in the jet fuel volatility negatively (positively) affect the real price of oil (policy-related economic uncertainty) for about 17 months (in the 5th month). As policy-related economic uncertainty heightens, the jet fuel volatility rises for more than a year. The dynamics shows that both oil price shocks and policy-related economic uncertainty innovations not only cause increases in the jet fuel volatility in the short run, but also significantly explain the overall variations in the oil/jet fuel price movement in the long run.

2.3.2. Impact of structural shocks on the real airline stock return

The last row of Fig. 2 shows that unexpected positive shocks to the price level of U.S. CPI cause a drop in the real airline stock

[13] The major approaches to factoring the coefficient matrix (A_0) include Doolittle, Crout, and Cholesky decompositions. The Cholesky decomposition is assumed to be relatively more efficient for the numerical solutions by Monte Carlo simulations.

[14] We acknowledge that the jet fuel volatility computed from history lag price changes. The specification attempts to mitigate the potential multicollinear issues of using both jet fuel prices and oil prices in the model. A test via the model $rpo_t = \sum_{i=0}^{24} \beta_i jfv_{t-i}$ shows that the absolute t-value of the coefficient estimate β_0 is 2.34, verifying that the volatility shocks of jet fuel prices lag the movement of the global real oil prices by more than 1-month at the 1% significance level.

[15] The restriction identification of VAR ordering is based on the the criticisms of VAR models that changing the order of variables in the VAR system would changes the results to be obtained.

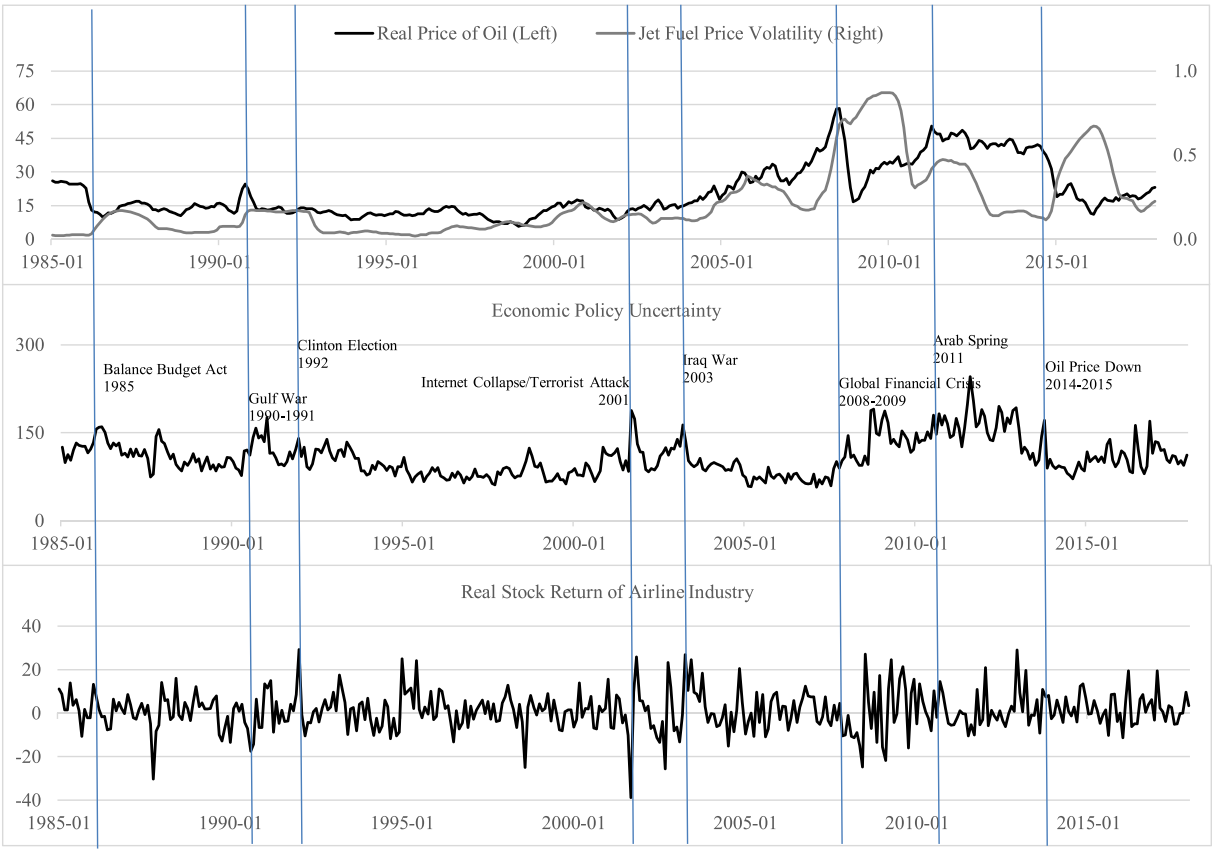

Fig. 1. Real Price of Oil, Jet Fuel Volatility, Economic Policy Uncertainty, and the Real Airline Stock Return.

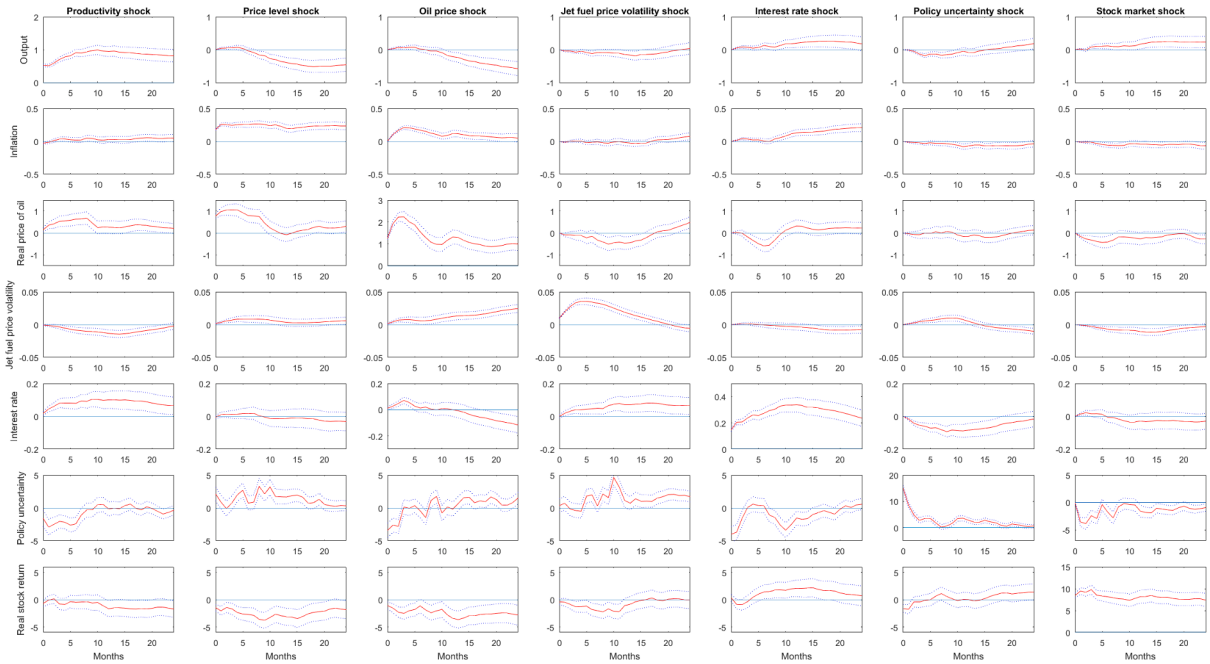

Fig. 2. Impulse Response Functions in the SVAR Model (1). Notes: The impulse response functions to one-standard deviation shocks are generated based on the SVAR model depicted in the text. Each row shows the effects of all structural shocks on a variable.

Table 1
Decomposition of Jet Fuel Price Volatility and Airline Stock Returns.

Panel A. Percent contribution to the variation of the jet fuel price volatility														
Horizon	Productivity Shock		Price Level Shock		Oil Price Shock		Jet Fuel Price Volatility Shock		Interest Rate Shock		Policy Uncertainty Shock		Stock Market Shock	
1	0.005	(0.32)	0.030	(1.04)	0.025	(0.79)	0.941	(19.79)	0.000	–	0.000	–	0.000	–
3	0.005	(0.32)	0.034	(1.01)	0.050	(1.10)	0.900	(14.58)	0.002	(0.56)	0.007	(0.94)	0.002	(0.44)
12	0.056	(0.94)	0.046	(0.83)	0.049	(0.74)	0.766	(7.06)	0.002	(0.10)	0.045	(1.03)	0.036	(0.92)
24	0.100	(1.30)	0.037	(0.76)	0.203	(1.91)	0.524	(4.50)	0.028	(0.52)	0.045	(1.20)	0.063	(1.22)
60	0.069	(1.13)	0.028	(0.61)	0.389	(3.39)	0.336	(3.27)	0.028	(0.47)	0.113	(1.81)	0.037	(0.92)
Panel B. Percent contribution to the variation of the real stock return of all airline companies														
Horizon	Productivity Shock		Price Level Shock		Oil Price Shock		Jet Fuel Price Volatility Shock		Interest Rate Shock		Policy Uncertainty Shock		Stock Market Shock	
1	0.006	(0.40)	0.028	(1.03)	0.015	(0.71)	0.002	(0.25)	0.001	(0.11)	0.034	(1.12)	0.914	(17.85)
3	0.011	(0.66)	0.034	(1.24)	0.023	(1.03)	0.004	(0.39)	0.018	(0.95)	0.054	(1.71)	0.856	(16.92)
12	0.026	(1.35)	0.048	(1.97)	0.049	(1.98)	0.016	(1.14)	0.033	(1.52)	0.061	(2.25)	0.768	(17.39)
24	0.029	(1.54)	0.055	(2.32)	0.054	(2.21)	0.034	(1.93)	0.034	(1.69)	0.064	(2.48)	0.731	(17.08)
60	0.030	(1.60)	0.056	(2.40)	0.055	(2.28)	0.035	(1.97)	0.036	(1.78)	0.063	(2.53)	0.726	(17.09)

Notes: The variance decomposition is calculated using the SVAR model depicted in the text.

returns. Rises in the oil prices negatively affect the real airline stock returns that reaches the lowest level about one year later. Unexpected shocks to the volatility of jet fuel prices significantly decrease the real airline stock returns in a window between 2 and 11 months. Unanticipated short-term interest rate innovations drive the real returns up in 6–16 months. Shocks to the economic policy uncertainty are negatively related to the real stock returns in the airline industry. Additionally, in 60 months, innovations in oil prices, jet fuel volatility, and policy-related economic uncertainty account for 5.5%, 3.5%, and 6.3% of the overall variation in the real airline stock returns respectively. Finally, over time, Fig. 3 shows that shocks to oil prices (jet fuel prices, policy-related economic uncertainty) account at times for more than 30% (56%, 23%) of the variation in real airline stock return in the period of Global Financial Crisis over 2008–2009.

Generally, the results confirm that global oil price and policy-related economic uncertainty interplay with the jet fuel volatility, with dynamics that significantly account for the overall variation in the real airline stock return. During the Global Financial Crisis, oil price shocks and policy-related economic uncertainty contribute most of the variation of the real airline returns (more than 30% and 23% respectively), whereas shocks to the volatility of jet fuel prices account for more than 56% with around one-year delay. In September 2001 because of the Terrorists Attack, the unanticipated shocks to the policy-related economic uncertainty explain more than 20% of the overall variation in the real airline stock returns.

2.3.3. Robustness check

We conduct two sets of robustness check in this subsection. First, we replace the airline stock return in the industry level by that in the firm level of four major airlines (Delta Air Lines, Southwest Airlines, United Airlines, and the American Airlines) in Model (1) respectively. Fig. 4 confirms that innovations in the jet fuel volatility lower the real airline stock return, whereas the largest impact effect is on the relatively smaller American Airlines. Table 2 presents that real prices of oil (fuel jet volatility) forecast between 4.4% and 9.6% (between 3.0% and 4.2%) of the four major airline stock returns.

Second, we introduce structural oil supply and demand shocks and investigate their effects on the real airline stock returns with the jet fuel volatility. We follow the recent literature of Kilian (2009), Kilian and Park (2009), and Peersman and Van Robays (2012) to include six variables in the model: the growth rate of world oil production (op_t), real economic activity index (rea_t) of Kilian (2009), real price of oil (rpo_t), jet fuel volatility (jfv_t), policy-related economic uncertainty (pu_t), and the real airline stock return in the industry level. (ret_t). Although unexpected shocks to U.S. industrial productivity have nonsignificant effects on the real stock returns of airline industry in Fig. 2, we find that unanticipated innovations in global aggregate demand have a statistically significantly positive effect on the real stock returns in Fig. 5. The result is consistent with that shown in Kilian and Park (2009) who argue that disentangling the underlying sources of oil shocks helps to assess the impact of increased oil prices on the stock market. However, Fig. 5 presents similar results as that in Fig. 2, in that the impact effects of real airline stock returns to jet fuel volatility innovations/oil market specific-demand shocks are statistically significantly negative in a window between 2 and 12 months.

3. Firm-level data analysis

Thus far our analyses have been mainly based on the airline industry-level data. As the macroeconomic variable shocks on the stock returns may vary across companies within the airline industry, the analyses can be conducted at the firm-level to understand different

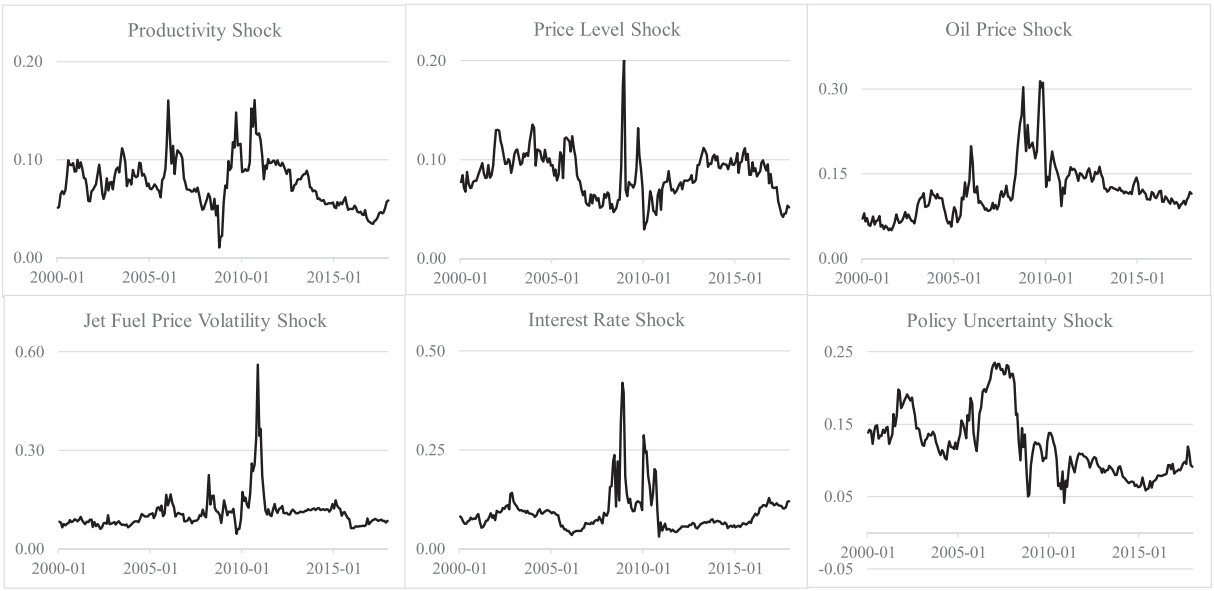

Fig. 3. Contributions to Forecast Error Variance of Real Stock Returns of Airline Industry from Structural Shocks.

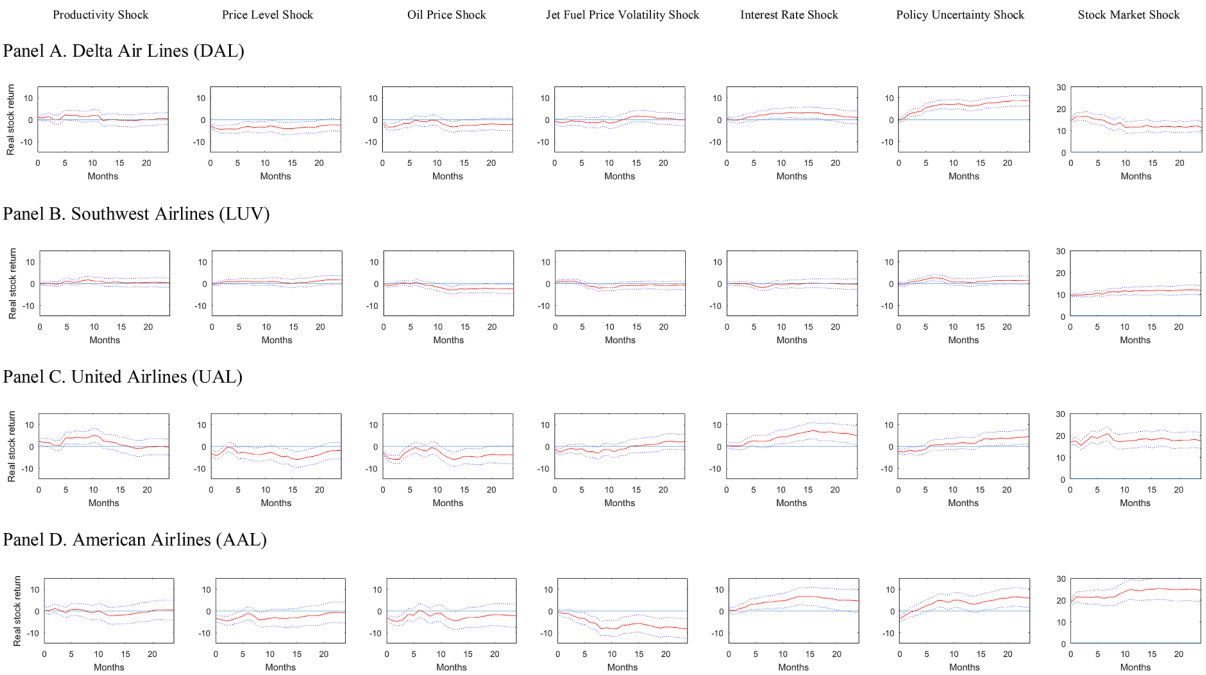

Fig. 4. Impulse Response Functions of Stock Returns of Major Airline Companies. Notes: The impulse response functions to one-standard deviation shocks are generated based on the SVAR model depicted in the text. Each row shows the effects of all structural shocks on a variable.

economic/policy implications and identify specific risk management strategies for individual airlines. For example, how does an airline company hedge future jet fuel purchase to manage its own fuel price risk/volatility specifically? To provide corroborative evidence to Section 2 at the industry-level data, we directly investigate how individual airline firm's stock returns and hedging strategies is associated with oil price shocks, jet fuel volatility and policy-related economic uncertainty in this section.

3.1. Data source

In the firm-level analysis, we use daily data from April 2, 1990 to December 31, 2017 that is subject to the availability of jet fuel spot prices. Following Bansal et al. (2014) we construct the rolling 22-trading-day volatility of daily jet fuel prices. The daily U.S. policy-related economic uncertainty is broad news-based economic policy uncertainty index from Baker et al. (2016). The daily stock returns in the firm level and daily oil spot prices are available at the U.S. Energy Information Administration and in the Compustat/CRSP merged Database respectively. We obtain the fuel hedging ratio for four major U.S. airline firms including Delta, Southwest, American, and United Continental Airlines. The hedging ratio data is drawn from the 10-K fillings at Electronic Data Gathering, Analysis, and Retrieval system (EDGAR) and is held constant over twelve months within a year. The monthly data is available from 1995 M1 to 2017 M12 in our hedging analysis.[16]

3.2. Methodology

3.2.1. Firm-level analysis

The firm-level analysis follows Narayan and Sharma (2011) to utilize a $GARCH(1,1)$ model[17] for each of the major U.S. airline firms as follows:

$$ret_t = \alpha_0 + \sum_{i=0}^{8} \beta_i grpo_{t-i} + \sum_{i=0}^{8} \gamma_i jfv_{t-i} + \sum_{i=0}^{8} \delta_i pu_{t-i} + \alpha_1 int_t + \alpha_2 ret_{mt} + \varepsilon_t \tag{2}$$

and the error term ε_t is of the following form:

$h_t^2 = \rho_0 + \rho_1 \varepsilon_{t-1}^2 + \rho_2 h_{t-1}^2$, $\varepsilon_t = h_t \omega_t$, and ω_t $N(0,1)$,where ret_t is the daily stock return for each airline in a day t, ret_{mt} denotes the

[16] Our sample is from 1995 to 2017 in the hedging analysis, which provides us with ample observations on the effects of changes in the hedging ratio on the stock returns over time. Cimadomo and D'Agostino (2015) discuss combining time variation and mixed frequencies in the analysis for interested readers.

[17] Hansen and Lunde (2005) show that GARCH (1,1) provides significantly better forecasts than a large number of parametric volatility models. However, estimates of a GARCH (p, q) model with higher orders of p and q may cause the AIC of BIC to select poor models that overfit.

Table 2
Percent contribution to the real stock return variation of major airline companies.

Panel A. Delta Air Lines (DAL)														
Horizon	Productivity Shock		Price Level Shock		Oil Price Shock		Jet Fuel Price Volatility Shock		Interest Rate Shock		Policy Uncertainty Shock		Stock Market Shock	
1	0.004	(0.27)	0.039	(1.30)	0.014	(0.69)	0.003	(0.20)	0.002	(0.22)	0.001	(0.14)	0.937	(22.21)
3	0.006	(0.38)	0.044	(1.44)	0.027	(1.11)	0.005	(0.31)	0.005	(0.48)	0.023	(1.25)	0.891	(19.12)
12	0.032	(1.58)	0.044	(1.75)	0.047	(1.95)	0.017	(1.03)	0.015	(1.05)	0.038	(2.01)	0.806	(17.64)
24	0.053	(2.21)	0.047	(1.95)	0.051	(2.13)	0.027	(1.45)	0.017	(1.22)	0.042	(2.19)	0.763	(15.98)
60	0.053	(2.23)	0.047	(2.00)	0.051	(2.17)	0.030	(1.55)	0.018	(1.26)	0.042	(2.21)	0.759	(15.83)
Panel B. Southwest Airlines (LUV)														
Horizon	Productivity Shock		Price Level Shock		Oil Price Shock		Jet Fuel Price Volatility Shock		Interest Rate Shock		Policy Uncertainty Shock		Stock Market Shock	
1	0.001	(0.13)	0.003	(0.21)	0.003	(0.28)	0.002	(0.23)	0.000	(0.01)	0.001	(0.13)	0.990	(42.75)
3	0.002	(0.18)	0.008	(0.58)	0.009	(0.61)	0.007	(0.65)	0.001	(0.05)	0.017	(1.02)	0.957	(32.52)
12	0.031	(1.69)	0.011	(0.77)	0.037	(1.85)	0.032	(1.95)	0.026	(1.50)	0.040	(2.19)	0.823	(21.73)
24	0.038	(2.02)	0.020	(1.34)	0.044	(2.20)	0.040	(2.25)	0.027	(1.60)	0.041	(2.27)	0.790	(19.97)
60	0.038	(2.06)	0.020	(1.38)	0.044	(2.23)	0.042	(2.32)	0.028	(1.66)	0.041	(2.30)	0.786	(19.73)
Panel C. United Airlines (UAL)														
Horizon	Productivity Shock		Price Level Shock		Oil Price Shock		Jet Fuel Price Volatility Shock		Interest Rate Shock		Policy Uncertainty Shock		Stock Market Shock	
1	0.015	(0.57)	0.032	(0.97)	0.022	(1.06)	0.005	(0.43)	0.001	(0.10)	0.016	(0.84)	0.910	(17.81)
3	0.014	(0.56)	0.041	(1.18)	0.046	(1.71)	0.015	(0.96)	0.001	(0.11)	0.019	(0.94)	0.865	(16.11)
12	0.047	(1.78)	0.064	(2.24)	0.089	(3.07)	0.029	(1.57)	0.012	(0.80)	0.026	(1.32)	0.733	(14.71)
24	0.062	(2.38)	0.075	(2.78)	0.094	(3.34)	0.036	(1.94)	0.018	(1.12)	0.031	(1.59)	0.685	(14.13)
60	0.062	(2.43)	0.075	(2.85)	0.096	(3.42)	0.037	(2.01)	0.019	(1.21)	0.032	(1.66)	0.679	(14.05)
Panel D. American Airlines (AAL)														
Horizon	Productivity Shock		Price Level Shock		Oil Price Shock		Jet Fuel Price Volatility Shock		Interest Rate Shock		Policy Uncertainty Shock		Stock Market Shock	
1	0.000	(0.00)	0.033	(1.27)	0.024	(1.11)	0.001	(0.07)	0.000	(0.05)	0.037	(1.32)	0.905	(20.77)
3	0.002	(0.22)	0.034	(1.32)	0.029	(1.26)	0.002	(0.24)	0.003	(0.27)	0.048	(1.67)	0.882	(19.69)
12	0.017	(1.09)	0.050	(2.01)	0.075	(2.84)	0.028	(1.48)	0.010	(0.71)	0.057	(2.28)	0.763	(17.06)
24	0.022	(1.40)	0.052	(2.22)	0.078	(3.03)	0.037	(1.76)	0.015	(0.98)	0.062	(2.56)	0.735	(16.16)
60	0.022	(1.42)	0.052	(2.28)	0.080	(3.14)	0.038	(1.80)	0.016	(1.04)	0.063	(2.65)	0.728	(15.89)

Notes: The variance decomposition is calculated using the SVAR model depicted in the text.

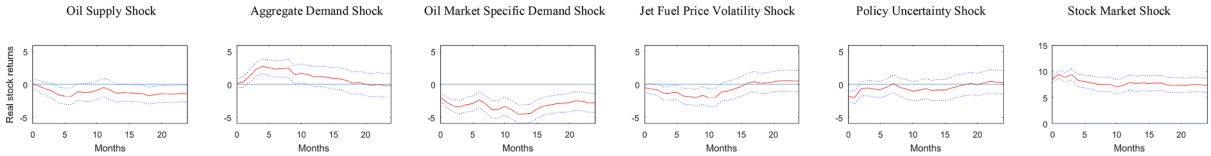

Fig. 5. Impulse Response Functions of Real Airline Industry Stock Returns to Structural Oil Price Shocks. Notes: The impulse response functions to one-standard deviation shocks are generated based on the SVAR model depicted in the text. Each row shows the effects of all structural shocks on a variable.

daily stock market return, int_t the interest rate, $grpo_t$ the percentage change in the crude oil prices, jfv_t the volatility of jet fuel prices, and pu_t the economic policy uncertainty index.

3.2.2. Hedging analysis

Within the airline industry, major airline companies hedge future jet fuel purchase to manage the fuel price risk/volatility. We follow Fama and French (2015) who recently show that stock returns are associated with five risk factors including the size, market, value, profitability, and the investment. Our model, testing the relation between stock returns and fuel hedging, includes control variables of the five factors and the variables of hedging ratio, real price of oil, volatility of jet fuel, and the economic policy uncertainty as follows:

$$ret_t = \alpha_0 + \sum_{i=1}^{24} \beta_i hr_{t-i} + \alpha_1 rpo_{t-1} + \alpha_2 jfv_{t-1} + \alpha_3 pu_{t-1} + \alpha_4 mrf_{t-1} + \alpha_4 smb_{t-1} + \alpha_5 hml_{t-1} + \alpha_6 rmw_{t-1} + \alpha_7 cma_{t-1} + \varepsilon_t \quad (3)$$

in which ret_t denotes the return of an airline stock in a month t, rpo_{t-1} the real oil prices in the previous period, jfv_{t-1} the jet fuel volatility, pu_{t-1} the economic policy uncertainty, mrf_{t-1} the market excess return, smb_{t-1} the return on small-minus-big stocks, hml_{t-1} the return on high-minus-low book value stocks, rmw_{t-1} the return on robust-minus-weak profitability stocks, cma_{t-1} the return on high-minus-low investment firms, and ε_t a zero-mean residual. In the dynamic analysis, we take the lag length $i = 24$ for the variable of

Table 3
Effects of oil price, jet fuel price volatility and economic policy uncertainty on airline stock returns.

	DAL($41B)	LUV($36B)	UAL($24B)	AAL($20B)	ALK($8B)	SKYW($3B)	ALGT($2B)	HA($2B)
Intercept	**−3.46**	−1.33	0.05	**5.52**	−1.29	−2.22	−1.22	3.56
Oil_t	**−13.59**	**16.98**	−1.13	−0.74	**−14.95**	**−11.00**	**−12.86**	**−12.14**
Oil_{t-1}	**−4.87**	−1.70	−0.10	−0.13	**−2.33**	−1.60	**−2.50**	**−2.00**
Oil_{t-2}	**−2.22**	0.72	−0.03	0.55	−1.71	0.48	−0.46	0.72
Oil_{t-3}	−0.71	−1.52	−0.06	0.38	−0.92	−0.80	−1.36	1.28
Oil_{t-4}	**−2.08**	−0.76	−0.13	−0.36	0.12	−1.75	−0.92	**5.28**
Oil_{t-5}	**−3.38**	0.67	−0.11	−0.08	0.58	0.64	−0.78	**2.89**
Oil_{t-6}	−1.82	−0.43	−0.23	−0.03	−0.49	−0.02	0.31	**−3.09**
Oil_{t-7}	−1.48	−0.45	−0.06	−0.09	−1.51	−0.12	−1.75	1.08
Oil_{t-8}	−0.05	−0.35	−0.13	0.09	−0.64	1.02	−0.09	−1.07
$JetFuel_t$	**2.31**	0.12	0.09	**−17.47**	0.52	−1.84	0.26	−1.01
$JetFuel_{t-1}$	0.41	−0.24	−0.16	1.78	−1.02	1.80	−0.63	−1.46
$JetFuel_{t-2}$	**−4.17**	0.78	−0.51	**2.59**	1.94	0.42	1.23	**2.81**
$JetFuel_{t-3}$	1.32	−0.09	0.43	1.06	−1.02	−1.32	−0.82	−1.22
$JetFuel_{t-4}$	1.72	−0.81	−0.02	0.98	−1.88	0.69	−1.27	−0.89
$JetFuel_{t-5}$	−0.61	0.41	−0.16	−1.52	1.80	−1.24	0.63	1.64
$JetFuel_{t-6}$	−1.59	1.65	0.45	1.66	0.09	**2.55**	0.66	0.50
$JetFuel_{t-7}$	0.96	−1.78	−0.01	1.27	−0.34	−1.50	1.25	−0.21
$JetFuel_{t-8}$	1.24	0.37	−0.18	**−5.32**	0.07	0.79	−1.53	−0.95
$Uncertainty_t$	−1.26	−0.05	−0.23	−0.40	**−2.03**	−0.74	1.26	−1.06
$Uncertainty_{t-1}$	0.78	0.61	0.13	−0.15	**2.37**	−0.51	0.29	**2.33**
$Uncertainty_{t-2}$	**4.20**	0.00	−0.02	−0.30	0.73	1.52	−0.51	**2.06**
$Uncertainty_{t-3}$	**2.13**	−0.24	0.12	−0.49	0.35	−0.57	−0.99	**−5.90**
$Uncertainty_{t-4}$	−0.36	−0.29	0.03	−0.56	0.17	0.52	−0.18	**−6.67**
$Uncertainty_{t-5}$	−1.39	1.92	−0.01	−0.66	−0.73	−0.27	0.88	**3.67**
$Uncertainty_{t-6}$	**−3.08**	−0.74	−0.03	−0.63	−0.21	0.44	−0.56	**−3.48**
$Uncertainty_{t-7}$	1.63	1.03	0.08	−0.61	0.61	0.38	0.75	−0.46
$Uncertainty_{t-8}$	1.05	−0.10	0.02	−1.00	−1.17	−0.24	−0.25	**4.85**
$Rate_t$	0.47	−0.37	0.00	−0.66	−1.04	0.10	0.88	−0.46
$MktReturn_t$	**52.70**	**60.44**	**4.13**	1.16	**60.09**	**48.84**	**24.61**	**37.04**
Schwarz criterion	33992.24	28174.47	48193.89	72042.59	29770.00	33592.82	11928.90	29380.79

Notes: The table shows the T-Statistics of regression coefficients of Model 2 based on the GARCH (1,1) model. Bold values denote statistically significant in 5% levels. We use daily data of oil prices, jet fuel prices, economic policy uncertainty, short-term interest rates, and the stock market returns and take 8 lags for oil prices, jet fuel price volatility, and the economic policy uncertainty in the regression. DAL($41B) denotes Delta Airline with the market value around $41 billion in September 2018, LUV Southwest Airline, AAL American Airline, UAL United Continental Airline, ALK Alaska Airline, SKYW Skywest, ALGT Allegiant, and HA the Hawaiian Airline.

hedging ratios (hr_{t-i}) for the possible delayed effects of fuel hedging on the airline stock returns.

3.3. Empirical results

3.3.1. Impact of oil prices and policy-related economic uncertainty on the airline stock return

Table 3 reports the impact of oil prices, jet fuel volatility, policy-related economic uncertainty on current major U.S. airline stock returns, including Delta, Southwest, American, United Continental, Alaska, Skywest, Allegiant, and the Hawaiian Airlines. Note that Table 3 shows the statistical significance based on Bollerslev and Wooldridge (1992), where the bolded numbers are the t-values that are statistically significant at 5% levels. Overall, around 88% (56/64) regression coefficients of oil prices have negative signs, the negative coefficients of jet fuel price volatility are as high as 53% (34/64), and over 64% (41/64) regression coefficients of policy-related economic uncertainty have negative signs, showing a generally negative shock effect presented in the SVAR analysis.

Table 3 presents that a rise in real oil prices consistently causes a reduced contemporaneous real return of airline stocks. The adverse effect with one-period lag is greatest based on the absolute t-value on Delta Airlines the largest airline firm by market capitalization, showing that investors are underreact to the public information (oil news) over the short horizon (e.g., Narayan and Sharma, 2011).

The negative coefficients of economic policy uncertainty are around 88% (7 out of 8) for the eight major U.S. airline firms either in the contemporaneous period or in one-period lag. Whereas the effect of policy-related economic uncertainty is greatest based on the absolute t-values on stock returns of Hawaiian Airlines the smallest airline firm by market capitalization, the policy uncertainty still affects returns in six lags for Delta Airlines and Hawaiian Airlines that is statistically significantly negative. In contrast, the effect of jet fuel volatility is greatest based on the absolute t-values on stock returns of American Airlines in the contemporaneous period and in eight-period lags. This effect is also highly statistically significant in two-period lags for Delta Airlines.

These results indicate that jet fuel price volatility and economic policy uncertainty affect firm returns differently even in the same airline industry. The negative effect of the jet fuel volatility and policy-related uncertainty on the real return of airline firms still exists at more than one-period lag, which confirms that investors underreact to the information uncertainty over the short-horizon.

3.3.2. The implications of jet fuel hedging for major US airline companies

Fig. 8 shows t-values of the regression coefficients of jet fuel hedging ratio (*i.e.*, percent of fuel requirement hedged in next year) with 1- to 24-month lags for four major U.S. airlines. The t-values of the regression coefficients of fuel hedging ratio do not show statistically significant for the largest firm, Delta Airlines. The t-values show statistically significantly positive for Southwest Airline in the 21st month. For United Airlines, the regression coefficients of fuel hedging ratio are significantly positive in the 11th and 22nd month and negative in the 12th and 24th month. The coefficients are positive in the 15th month for the relatively smaller U.S. airline American Airlines.

The results confirm that hedging future fuel purchase has an effect on real airline stock returns. The significant effect is delayed by around ten months and is pronounced for relatively smaller airlines Southwest Airlines, United Airlines and American Airlines. Hedging future fuel purchase consistently has statistically positive impact on the smaller airlines Southwest Airlines and American Airlines. It suggests that investors value airline hedging future fuel purchase in line with the findings that hedging affect firm value (Carter et al., 2006).

4. Alternative oil price measures and the impact of COVID-19 on the airline industry

To establish the robusteness of the result that the intensity of the oil price shock effects on the airline stock returns, we utlize alternative forms of crude oil prices in Model (1) such as the first-differenced oil prices in Fig. 6 and West Texas Intermediate (WTI) oil prices Fig. 7. Both Figs. 6 and 7 show that innovations in the oil prices have a statistically significantly negative effect on the airline stock returns. Second, the alternative jet fuel price volatility is the standard deviation of 12-month rolling samples by using the prices of U.S. refiners' kerosene-type jet fuel sales to end consumers. We obtain similar results that unexpected shocks to jet fuel price volatility cause negative effects on the stock returns of airline industry.

In early 2020 we witnessed that the spread of the New Coronavirus (COVID-19) caused the contractions of real economic activity worldwide, for example the sharp declines in the airline stock prices. Here we open the avenue for the future investigation of the interesting and demanding topic to extend the nexus of airline stock returns and the policy-related economic uncertainty triggered by the major events of Coronavirus pandemic (COVID-19) fear and oil price crashes in 2020, partially due to the limitation on firm-level data by early 2020.[18] From February 2020 to March 2020 because of the COVID-19 news, WTI oil prices drops 42.2%, jet fuel price declines 36.85%, economic policy uncertainty index jumps 76.40%, and the airline stock returns decline substantially, for example, AAL 55.70%, DAL 60.57%, LUV 29.72%, and UAL 54.84%. The observations provide us with further evidence on the strong connection of economic uncertainty, oil price shocks, and the stock returns in the airline industry.

[18] We draw the firm-level data from the Compustat Merged Database/Center for Research in Security Prices (CRSP) via Wharton Research Data Services (WRDS). The hedging ratio data is drawn from the 10-K fillings at Electronic Data Gathering, Analysis, and Retrieval system (EDGAR). Unfortunately, there is one-year delay for the dataset, not available for the year of 2020.

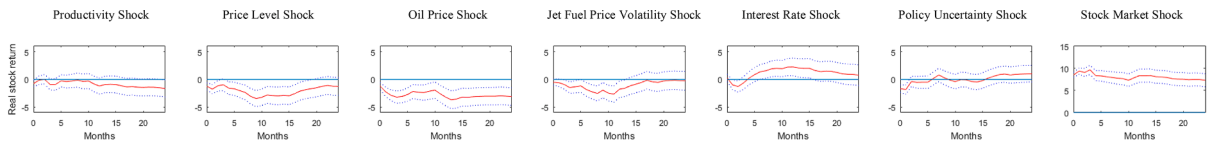

Fig. 6. Impulse Response Functions in the SVAR Model (1) using First-Differenced Oil Prices. Notes: The impulse response functions to one-standard deviation shocks are generated based on the SVAR model depicted in the text. Each row shows the effects of all structural shocks on a variable.

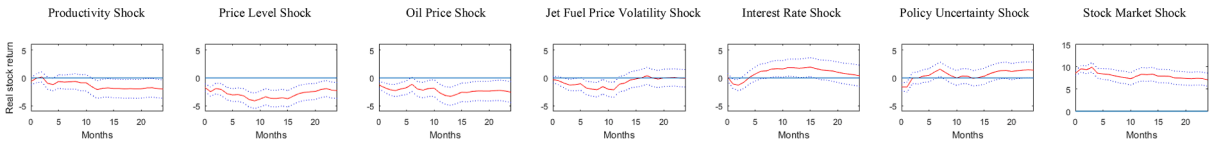

Fig. 7. Impulse Response Functions in the SVAR Model (1) using WTI Oil Prices and 12-Month Jet Fuel Volatility Notes: The impulse response functions to one-standard deviation shocks are generated based on the SVAR model depicted in the text. Each row shows the effects of all structural shocks on a variable.

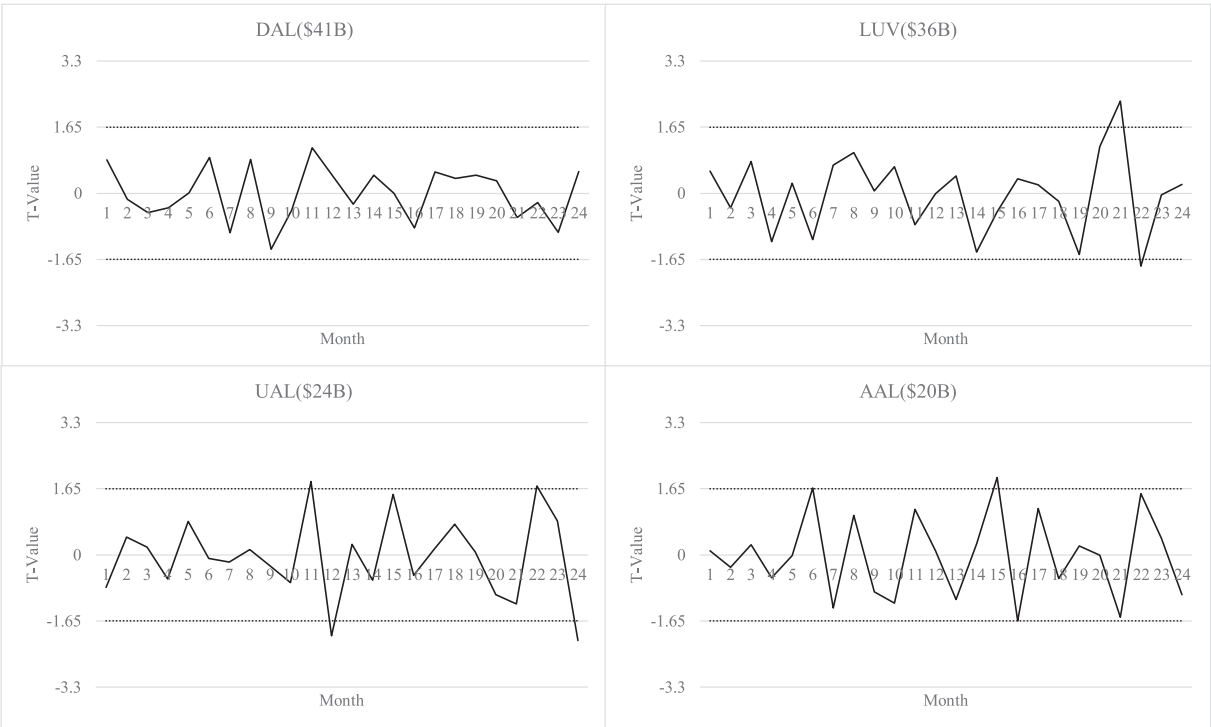

Fig. 8. T-Values of Regression Coefficients of Jet Fuel Hedging Ratios.

5. Concluding remarks

This study employs a structural vector-autoregressive model to examine the impact of jet fuel volatility on the real stock returns of U.S. airline industry and of U.S. major airline companies with oil prices and policy-related economic uncertainty. The results are the following. First, oil price shocks and policy uncertainty innovations cause volatility of jet fuel prices to rise. Uncertainty about jet fuel prices in turn lowers the real oil prices and raises the policy-related economic uncertainty with a delay. 38% and 11% of the variation in the jet fuel price volatility are explained by oil price shocks and policy-related economic uncertainty innovations respectively. Second, jet fuel volatility interplays with crude oil price shocks and policy-related economic uncertainty, which in turn significantly accounts for the overall variation in the real airline stock return. During 2008–2009 Global Financial Crisis, oil price shocks and the policy uncertainty innovations contribute most of the real stock return variations (more than 30% and 23% respectively), whereas shocks to the volatility of jet fuel prices account for more than 56% with around one-year delay. In September 2001 because of the Terrorists Attack, the unanticipated shocks to the policy uncertainty explains around 20% of the real airline stock return variations.

Third, robustness results consistently confirm that positive shocks to oil prices/the volatility of jet fuel prices cause a decreased major airline returns in the U.S. Innovations in the jet fuel volatility have the largest adverse effect of the real stock returns of the American Airlines.

Using firm-level daily data, we further investigate the oil price-return nexus for major airline firms in the U.S. (Delta, Southwest, American, United Continental, Alaska, Skywest, Allegiant, and Hawaiian Airlines). In general, the firm-level evidence is consistent with the SVAR estimates that the impact of oil prices, jet fuel volatility, and policy-related economic uncertainty on the airline firm returns are negative. The negative effect exists in the contemporaneous period and at more than one-period lag, which suggests that investors likely underreact to the public information of oil news and the economic uncertainty over the short-horizon. Investors value hedging future fuel purchase which affects the airline stock returns.

In summary, this paper provides both aggregate and firm-level evidence on the impact of oil prices (economic uncertainty and jet fuel volatility) on selected U.S. airlines, and analyzes the role of hedge future jet fuel purchase to manage the fuel price risk. Our empirical evidence provides specific knowledge of U.S. airline industry and have several policy implications for practitioners, managers of airline industry, operators of crude (and jet fuel) consumption and institutional, private and also commodity investors. First, it is well known the relevance of crude oil price dynamics for global economy, financial markets and specific industries. This paper corroborates that crude oil price dynamics as well as jet fuel volatility are crucial for U.S. airline industries. Second, this study also finds evidence that policy-related economic uncertainty negatively affects airline industry returns. Managers of airline industry, institutional and private investors should follow the policy uncertainty as one of the major drivers of stock returns in the airline industry. Third, the empirical evidence also indicates that airline industry should hedge jet fuel price risk for smallest airline firms.

This study opens several avenues for the future investigation. The first important topic for future research is related with international evidence instead of U.S. evidence. Second, our empirical evidence shows that hedging future fuel has positive impact on the smaller U.S. airlines. It also would be interesting extend our results considering local versus international air routes. Finally, the interesting and demanding topic for the research in the oil market would extend the nexus of airline stock returns and the policy-related economic uncertainty triggered by the major events of Coronavirus pandemic (COVID-19) fear and oil price crashes in 2020.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Dataset description

Variable	Minimum	Mean	Maximum	Data Range	Data Source
Industrial Productivity (IP)	56.264	85.701	107.299	1985 M1 – 2017 M12	Federal Reserve Economic Data (FRED)
Consumer Price Index (CPI)	105.700	177.960	247.910	1985 M1 – 2017 M12	Federal Reserve Economic Data (FRED)
Oil Production (OP, million barrels)	51,324	68,129	82,304	1985 M1 – 2017 M12	Department of Energy
Real Economic Activity Index (REA)	−163.743	−0.030	187.663	1985 M1 – 2017 M12	Kilian's (2009) Personal Webpage
Real Price of Oil (RPO)	5.712	20.990	58.338	1985 M1 – 2017 M12	Department of Energy
Jet Fuel Price Volatility (JFV)	0.019	0.213	0.872	1985 M1 – 2017 M12	Department of Energy
3-Month T-Bill Interest Rate (INT)	0.010	3.367	8.820	1985 M1 – 2017 M12	Federal Reserve Economic Data (FRED)
Economic Policy Uncertainty (PU)	57.203	107.907	245.127	1985 M1 – 2017 M12	Baker et al.'s (2016) Economic Policy Uncertainty Index Webpage
Market Excess Return (MRF, %)	−17.230	0.714	11.350	1995 M1 – 2017 M12	Fama-French Data Library
Small-minus-Large Size Stock Return (SMB, %)	−14.940	0.175	18.380	1995 M1 – 2017 M12	Fama-French Data Libary
High-minus-Low Value Stock Return (HML, %)	−11.100	0.204	12.900	1995 M1 – 2017 M12	Fama-French Data Library
Robust-minus-Weak Profitability Stock Return (RMW, %)	−17.990	0.348	12.820	1995 M1 – 2017 M12	Fama-French Data Library
Low-minus-High Investment Stock Return (LMH, %)	−6.880	0.230	9.580	1995 M1 – 2017 M12	Fama-French Data Library
Airline Industry Stock Return (RET, %)	−38.500	1.281	29.337	1985 M1 – 2017 M12	Center for Research in Security Prices (CRSP) and Compustat Merged Database
Delta Hedging Ratio/Stock Return (%)	0.000/-93.333	0.321/0.044	0.800/90.278	1995–2017/1990 M4 – 2017 M12	

(*continued on next page*)

(*continued*)

Variable	Minimum	Mean	Maximum	Data Range	Data Source
					Electronic Data Gathering, Analysis, and Retrieval system (EDGAR)/Center for Research in Security Prices (CRSP) and Compustat Merged Database
Southwest Hedging Ratio/ Stock Return (%)	0.020/-26.571	0.498/ 1.541	0.900/ 35.000	1996–2017/1990 M4 – 2017 M12	Electronic Data Gathering, Analysis, and Retrieval system (EDGAR)/Center for Research in Security Prices (CRSP) and Compustat Merged Database
American Hedging Ratio/ Stock Return (%)	0.000/-87.833	0.215/ 2.161	0.480/ 93.333	1997–2017/1990 M4 – 2017 M12	Electronic Data Gathering, Analysis, and Retrieval system (EDGAR)/Center for Research in Security Prices (CRSP) and Compustat Merged Database
United Hedging Ratio/Stock Return (%)	0.000/-97.46	0.143/ 0.719	0.750/ 78.616	1998–2017/1990 M4 – 2017 M12	Electronic Data Gathering, Analysis, and Retrieval system (EDGAR)/Center for Research in Security Prices (CRSP) and Compustat Merged Database

Notes: The Appendix presents the variables, data range, and data source described in the text.

Appendix B. Economic policy uncertainty index

The monthly U.S. economic policy uncertainty index available from January 1985 is developed by Baker, Bloom and Davis (2016). The index of overall economic policy uncertainty is a weighted average of four uncertainty components: news-based policy uncertainty, CPI forecast interquartile range, tax legislation expiration, and federal expenditures forecast interquartile range. Baker, Bloom, and Davis (2016) set the weights to 1/2 on the news uncertainty and 1/6 on each of taxation expiration, CPI disagreement, and expenditure dispersion components. The news-based policy uncertainty reflects the newspaper coverage of U.S. economic policy uncertainty, constructed by the month-by-month searches of Google news for articles containing the term 'uncertainty' and economic (e.g., monetary and fiscal) policies. The number of articles that discuss both the economy and policy uncertainty each month quantify as news uncertainty in that month. The raw counts about the news uncertainty are normalized by the number of news articles that contain the term 'today' in order to mitigate the volume accumulation and high-frequency noise problems. The other components of overall policy uncertainty are not news based. The CPI disagreement and Federal expenditure dispersion are measured by the forecasters' disagreement (the interquartile range of forecast) over future outcomes about inflation rates and federal Government purchases, respectively. The quarterly raw data of the forecast about inflation rates and Federal Government purchases are drawn from the survey of professional forecasters of Federal Reserve Bank of Philadelphia. The index value of monthly CPI disagreement and expenditure dispersion is held constant for each quarter. The taxation expiration is a 'transitory measure' constructed by the number of temporary federal tax code provisions set to expire in the contemporaneous calendar year and future ten years and reported by the Joint Committee on Taxation. The quarterly raw data of the forecast about inflation rates and Federal Government purchases are drawn from the survey of professional forecasters of Federal Reserve Bank of Philadelphia. The index value of monthly CPI disagreement and expenditure dispersion is held constant for each quarter.

The daily U.S. policy-related economic uncertainty available from January 1, 1985 is also developed by Baker, Bloom and Davis (2016). It is a daily news-based economic policy uncertainty index based on newspapers in the United States from the NewsBank Access World News database. The measure of the index is the number of articles that contain at least one of 3 sets of terms: economic or economy, uncertain or uncertainty, legislation or deficit or regulation or congress or Federal Reserve or White House. Both monthly and daily economic policy uncertainty index are available from https://www.policyuncertainty.com/index.html.

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