# Oil Prices and Banking Instability: A Jump-Diffusion Model for Bank Capital Structure

*Willi Semmler*[a] *and Samar Issa*[b]

**ABSTRACT**

We develop an empirical model of bank capital structure to study the impact of large oil shocks on overleveraging of banks which presents severe challenges for banks' balance sheet management. The measure of overleveraging builds on the Stein (2012) model by adding a jump-diffusion component that captures the jump size and intensity of predictors such as oil prices and political instability. Overleveraging is derived and estimated for a sample of six banks in three oil-producing countries and Western countries using the Markov Chain Monte Carlo (MCMC) method, for the years 2006–2016. The estimation of the optimal debt shows that most of the banks in this context had a high optimal debt around 2008, overlapping with the oil price shock. In addition, most of the predictors, namely oil prices and political instability factors proxied by terrorism, political corruption, and military expenses, regularly appeared in volatility and jump intensity factors.

**Keywords:** Overleveraging, Banking instability, Banking sector, Real economy, Oil prices, Oil shocks, MCMC, Jump-diffusion, Jump risk

https://doi.org/10.5547/01956574.40.SI2.wsem

## 1. INTRODUCTION

This paper contributes to recent academic research on the topic of overleveraging and the effects of large oil and political instability shocks on asset prices, financial markets, and the balance sheets of banks. We show that those shocks might be destabilizing rather than mean reverting. In order to capture the large oil policy shocks, we introduce a jump-diffusion process into the type of banking model as proposed by Stein (2012) and further extended by Gross, Henry, and Semmler (2017). In our paper, we are dealing with the oil market and the volatility of oil prices in terms of a jump-diffusion process that not only helps one understand and stylize how the commodity market is affected, but also how the stability of the banking system is influenced. The theoretical model, the measuring of optimal debt of banks, the use of the MCMC methodology in this framework, and the empirical results contribute to the existing studies, as the different components of the jump-diffusion model are significant and have, in relevant cases, expected signs. Moreover, the results on the disparity in the behavior of different components among countries constitute an added value of the paper. Commodity futures prices and options prices are frequently treated as a jump-diffusion process. For instance, Hilliard and Reis (1999) show empirical evidence that jump diffusion models are most suitable for commodity price estimation due to the stochastic nature underlying the commodity markets. Moreover, the use of jump-diffusion models for commodity option and futures markets goes back

a Department of Economics, New School for Social Research, and Bielefeld University.

b Corresponding author. Department of Economics and Finance, Saint Peter's University. E-mail: sissa@saintpeters.edumailto:sissa@saintpeters.edu.

 Copyright © 2019 by the IAEE. All rights reserved.

a long time. Jump-diffusion processes have actually become a standard modeling tool in commodity and energy derivatives markets since Merton's (1976) pioneering work. Later on, Bates (1991, 1996) has extended the model and developed a jump-diffusion model that permits jump risk to be systematic, by allowing jumps in the asset return process. On the other hand, Duffie et al. (2000) allow jumps both in the asset return process and in the variance process. In oil-producing countries, much of the commodity price jumps are intensively felt in the banking system. Oil-producing countries are exposed to global financial markets, which are affected by the changes in oil prices. In oil-exporting countries, the banks can be resilient to direct oil price changes; however, financial strains may eventually intensify (Baffes et al., 2015).

Several researchers agree that there exists a connection between overleveraging and the oil market. For example, an interesting discussion on the credit cycle connection with oil and commodities markets is presented by Kablan et al. (2017). The authors take a sample of African commodity exporters and apply a co-spectral analysis, as opposed to time series analysis. They find that in exporting countries, credit expansion is a result of commodity price booms, which in turn increases the capital inflows and liquidity. They also show that during price booms and troughs, one can more readily see the correlation between credit cycles and crude oil indices. Another study by Ftiti et al. (2016) examines the commodity prices and the private sector credit, by using wavelet analysis on a sample of three commodity-exporting nations in Sub-Saharan Africa. The authors find that the length of the time span affects the relationship between credit and commodities. For instance, they are strongly related over long timescales, while over short/medium timescales, the interdependence is only pronounced during economic turmoil.

When we speak about overleveraging, we are actually referring to lending booms. It is well known that lending booms may precede banking system instability, because they imply increased risk-taking in the financial system. This has the potential to result in financial turmoil if the economy is hit by a negative, adverse shock in asset prices, as occurred during the crisis of 2008. Many studies have investigated issues related to asset price channels through which the banking system's instability is triggered. Some of these important academic contributions include: Brunnermeier and Sannikov (2014), Mittnik and Semmler (2012a, 2013), Stein (2011, 2012), and Gross, Henry, and Semmler (2017).

Brunnermeier and Sannikov (2014) focused specifically on the banking sector. The authors stated that a shock to asset prices created a vicious cycle through the balance sheets of the banks. In other words, risk-taking and excessive borrowing occurred when asset prices were rising. According to Mittnik and Semmler (2012a, 2013), the unconstrained growth of capital assets through excessive borrowing, facilitated by the lack of regulations imposed on financial intermediaries, was considered the main cause for banking sector instability. On the other hand, large payouts by the banking managers, with no "skin in the game", affected banks' risk-taking behaviors, equity development, and leveraging. In summary, the increased risk spreads and risk premia, especially at a time when defaults begin, exposed banks to vulnerabilities and financial stress triggered by security price movements.

Stein (2011, 2012) argues that the destabilizing mechanism results from a link between asset prices and borrowing. He specifies that overleveraging begins when assets that are held by banks become overvalued. Above average returns, due to housing prices that increase owners' equity, induce a greater demand by banks for mortgages and funds. Thus, banks enjoy capital gains above some normal returns and begin to become overleveraged compared to optimally leveraged. The basis of Stein's model is that the optimal capital structure reflects the threshold beyond which net worth declines. His analysis is based on the assumption that

All rights reserved. Copyright © 2019 by the IAEE.

the mean interest rate exceeds long-term capital gains, a constraint that he refers to as "no free lunch." Therefore, for overleveraging to occur, a violation of this constraint should take place. Stein suggests using the trends/drifts in capital gains and interest rates to measure optimal debt better. He also defines excess debt as the difference between the actual and optimal debt.

This paper presents an extended model of bank capital structure, which originates from Stein's (2012) model, but goes a step further to include a jump-diffusion term that aims at capturing the mechanism between the sustainable leverage of a bank and various oil-related, politically-related, and regulation-related events that drive asset prices and bank returns contributing to frequent portfolio value volatility and rebalancing. To study this issue, we focus on oil-producing and oil-importing countries, the former in the Middle East and the latter in the Western hemisphere. Our approach builds on Stein's (2012) model by adding a jump-diffusion component that captures the jump size and intensity of oil prices and political instability predictors. The optimal debt is derived and then estimated for a sample of six banks in three countries for the period of 2006 to 2016. We employ the banks' balance sheet dynamics of Stein (2012) and build in the aforementioned jump-diffusion process. The idea of excess debt is pursued further in Gross, Henry, and Semmler (2017), while Semmler and Parker (2017) examine the dynamics of the wealth disparity using the same model by Stein (2012).

The purpose of this paper is to present an original theoretical jump-diffusion model of bank capital structure. We further demonstrate the use of the MCMC methodology in a new framework to estimate this model of banking instability when encountered by stochastic shocks, and an empirical estimation applied to Bahrain, the United States, and the United Kingdom. This paper, therefore, contributes to the literature by illustrating the added value of surpassing the traditional estimation of bank leverage, which has been the norm thus far, and adding oil prices and political instability as major elements in the model. The idea of the model is to present the cash flow function of the banks as the difference between incoming and outgoing cash flows, as well as to emphasize study of the portfolio holdings when the banks invest following a jump diffusion model.

The remainder of the paper is organized as follows: Section 2 discusses the background and the descriptive analysis related to oil prices. Section 3 presents the rationale and motivation behind the theoretical model used herein. Section 4 describes the methodology and the data used in this study to illustrate the problem and to answer our research question, as well as the findings and the policy implications. Section 5 concludes the paper.

## 2. STYLIZED FACTS AND RELATED LITERATURE

Historically, periods of oil price shocks were followed by or have basically caused recessions, periods of excessive inflation, low productivity, and low economic growth as mentioned by several researchers; see Darby (1982), Hamilton, J. D. (1996), and Burbidge, J., & Harrison, A. (1984). Moreover, detailed studies on oil price movements as a predictor for low growth and recessions can be found in works by James Hamilton. For instance, Hamilton (2008) emphasizes the relationship between oil price swings and the macroeconomy in the U.S., and states that oil shocks directly increase unemployment and decrease income level. In addition, he shows that a reduction in real GDP growth leads to a much stronger reduction in the demand for new homes and an increase in delinquency rates. Moreover, Hamilton (2011b) shows that oil price increases are the reason behind ten recent recessions in the U.S., leaving only a single recession not being associated with an increase in oil prices. On the other hand, Gilje et al. (2017) present a novel method for analyzing the effect of oil prices on the financial market. The authors find that natural gas shale discoveries

Copyright © 2019 by the IAEE. All rights reserved.

positively influence the financial market through a chain of positive reactions originating from the increase in local credit supply due to the increase in bank deposits. This, in turn, creates a credit boom which blossoms the industries that rely on debt financing, mainly in lending markets dominated by small banks. Similarly, Kilian, L. (2008) investigates the oil price shocks' effect on the macroeconomy and finds that positive oil shocks have been unsuccessful in causing a recession in the U.S., since increases in oil prices were mostly determined by global aggregate demand shocks.

Herein, we put greater emphasis on the banking system, and more specifically, on the modeling of the optimal leverage of a bank, a topic that has not yet been greatly analyzed. The banking system is highly affected by oil price shocks. For instance, during the 1970s, the United States' banking system served as an intermediary between oil-exporter surpluses and emerging-market borrowers in Latin America and elsewhere. This petrodollar recycling, which was initially viewed as correct behavior, actually led to the 1980s debt crisis. Generally speaking, increases and decreases in oil prices do affect the banking sector, especially in economies that are highly dependent on oil and gas exports. Moreover, macro-financial linkages can amplify the effects of oil price movements over the financial cycle. More specifically, oil price swings, in addition to government spending policies, create feedback loops between asset prices and credit, which can increase the systemic risk in the overall financial sector of a certain economy. An IMF paper by Khandelwal, Miyajima, and Santos (2016) analyzes the effects of oil prices on the banking sector in the Gulf Cooperation Council (GCC). The authors argued that an increase in oil prices leads to higher oil revenues and stronger fiscal and external positions. In turn, this positively affects equity market returns since investors expect the impact of higher oil prices to be positive on the corporate sector, and eventually expect more government spending. Consequently, banks become more liquid, and credit growth increases as real estate prices increase. Thus, this places the banks' balance sheets in a much stronger position as asset prices appreciate. A recent IMF working paper by Eberhardt and Presbitero (2018) states that banking crises are potentially driven by commodity price changes. The authors employ a sample of 60 low-income countries for the years 1981 to 2015 and show that credit growth can't be considered a main driving force of economic distress or financial crisis, as most literature states, since it is mediated through capital inflows, which are also fueled by a booming financial market. The relation of credit flows, output, and oil prices is documented and analyzed in Appendix A.

It should be noted that the correlation and causality from oil price to the banking sector (a concept supported by the works of Khandelwal, Miyajima, and Santos (2016) and Eberhardt and Presbitero (2018)) assess the intuitive case of oil-exporting countries only. Further empirical investigation on oil-importing countries is necessary in order to generalize this correlation between oil prices and the banking industry.

## 3. THEORETICAL MODEL

In this section, an extended model of bank capital structure is presented to estimate the optimal debt policy of a bank, or of a similar entity, for which portfolio jumps may occur for several reasons, leading to frequent portfolio rebalancing. Our work is inspired by the framework of Stein (2012), in which optimal leveraging decisions can be made independently over time if a logarithmic utility function is used. However, Stein's work should be extended if applied to oil-dependent countries. Major hazards for a domestic bank in an oil-exporting market include, but are not limited to, sudden jumps in domestic stocks and domestic currency, liquidity crunches, news about the Organization of the Petroleum Exporting Countries (OPEC) fixing oil prices or negotiations, revisions in the outlook for domestic real estate, and sanctions or trade wars, such as the sanctions imposed on Qatar.

All rights reserved. Copyright © 2019 by the IAEE.

All of these events can lead to jumps in investment portfolios. The magnitude of jumps is random, but can be larger than portfolio fluctuations preceding such jumps. Therefore, all portfolio fluctuations cannot be described by one volatility number, and a separate jump component must be added to the equation for the dynamics of the investment portfolio price. Moreover, Stein (2012) posits that interest rate shocks are highly negatively correlated with capital gain shocks. These details are neglected here because Stein's equation for the interest rate disguises the true determinants of the optimal leverage decisions if such decisions are made frequently. Highly nonlinear shapes of the mechanism are allowed, and the calculation of optimal leverage is derived under broad assumptions in the presented model.

The model focuses on the capital structure of a bank. At time t, the bank has the total net worth of $X(t)$. Additionally, the bank borrows $f(t) * X(t)$, where $f(t)$ is known at time t. Thus, $f(t)$ is the leverage ratio and equals debt over equity, and thus $f(t) * X(t)$ are the liabilities, and $(1+f(t)) * X(t)$ are the assets.

The bank has the following incoming and outgoing cashflows. First, the bank invests its assets into portfolio $P$. The price of the portfolio fluctuates randomly and equals $P(t)$ at time t. Second, the bank pays interest on liabilities, which is continuously compounded at a rate $i(t)$. The interest rate $i(t)$ is generally treated as a stochastic process. In this paper, it is assumed that the interest rate is set at the beginning of the accrual period and the front end of the term structure is flat. In other words, at every moment of time t, interest rate $i(t)$ applies to interest paid over the interval $[t, t+dt]$ for small values of $dt$. Third, the bank spends a fraction of its net worth continuously at a rate $C$. The rate is fixed and deterministic.

The sum of the cashflows implies the following stochastic differential equation (SDE) for $X(t)$:

$$d[X(t)] = X(t) * \left[ (1+f(t)) * \frac{d[P(t)]}{P(t)} - f(t) * i(t) * dt - C * dt \right] \tag{1}$$

As compared to Stein (2012), this model is original in the assumptions it makes about rates and the portfolio price. Let $Z(t) = (t, i(t), S(t), O(t), I(t))$ be the state process, where $t$ is time, $S(t)$ is the level of S&P 500, $O(t)$ is the price of oil, and $I(t)$ is an indicator of political stability in the region. The value of $Z(t)$ is completely known at time $t$. Some of its components may be observed even earlier. For example, they can be lagged versions of well-established indicators. The portfolio price $P(t)$ is given by:

$$d[P(t)] = P(t) * [A(Z(t)) * dt + B(Z(t)) * d[W(t)] + d[M(t)]] \tag{2}$$

Additionally, $A()$ and $B()$ are deterministic functions, $W(t)$ is a Brownian motion. $M(t)$ is a compound counting process, i.e. $d[M(t)] = U(t) * d[N(t)]$. $N(t)$ is a counting process with intensity $\lambda(t) = \Lambda(Z(t))$, referred to as jump intensity, conditional on $\lambda$ and $N(t)$ is otherwise independent. Furthermore, $U(t)$ is a random variable with distribution function $G(u \mid Z(t))$. In other words, $P(t)$ is a jump-diffusion process, where the amplitudes of jumps are random and almost all distributional characteristics are allowed to change over time via their dependence on $Z(t)$. Note that the compound counting process $M(t)$ may represent several compound counting processes related to events of different types. For example, $P(t)$ may jump due to revisions in the outlook for domestic markets, changes in interest rates, or political events.

Copyright © 2019 by the IAEE. All rights reserved.

Substituting equation 2 into equation 1, we can write the dynamics of $X(t)$ as:

$$d[X(t)] = X(t)*[(1+f(t))*A(Z(t))*dt + B(Z(t))*d[W(t)] + d[M(t)]) - f(t)*i(t)*dt - C*dt]$$

$$d[X(t)] = X(t)*\{[(1+f(t))*A(Z(t)) - f(t)*i(t) - C]*dt + (1+f(t))*B(Z(t)) *d[W(t)] + (1+f(t))*d[Y(t)]\} \quad (3)$$

The formula above is split into a drift term, diffusion term, and jump term. The jump term may seem like a theoretical extension at first; however, it is important since market changes often occur in sudden jumps rather than in a diffusive manner. Moreover, the normality assumption is not necessary in our model. Furthermore, we assume that the bank maximizes logarithmic utility; therefore, at every moment of time $t$, the optimal leverage is value $f^*(t)$ maximizing:

$$[(1+f(t))*A(Z(t)) - f(t)*i(t) - \frac{1}{2}*(1+f(t))^2*B(Z(t))^2 + \lambda(Z(t))*\int_{-\infty}^{+\infty}\log(1+(1+f(t)*u)dG(u\,|\,Z(t)) \quad (4)$$

The proof of the derivation of the optimal leverage largely follows the line of thought in section 4.9 of Stein (2012), but it has nuances of its own, such as the use of logarithm which comes from the benefit of getting solutions without dynamic programming. The derivation is presented in Appendix C.

## 4. ESTIMATION OF THE OPTIMAL DEBT

We undertake our estimations by using daily data for three countries, namely Bahrain, the United States, and the United Kingdom, for the period of 2006 to 2016.

### 4.1 Data set

The data sets consist of information on three levels of aggregation: bank, country, and supra-national (i.e., oil prices common to all countries).

Bank-specific data are obtained from the balance sheets and income statements of six banks in the three countries mentioned above. These six banks are National Bank of Bahrain and Salam Bank in Bahrain, Lloyds and Barclays in the United Kingdom, and Bank of America and Wells Fargo in the United States. Banks have been chosen based on their market size, as well as their asset price behavior and their short-term and long-term debt for the years prior to and following the crisis. Since optimal debt and asset prices are one of the main themes of the paper, they were elements of consideration. The data collected are quarterly data, but have been converted by means of quadratic match average method, so that all time series data are available at daily frequency. These bank-level variables consist of Total Assets, Total Liabilities, and Total Operating Expenses. Moreover, all of the banks in the sample are publicly traded, and therefore, daily stock prices for the six banks are collected from Bahrain Bourse, Yahoo Finance, and Marco Trends. Data is found in Appendix D.

The country-level variables are obtained from several resources. First, the 3-year treasury yield is used as a proxy for the interest rate and is obtained from the IMF's International Financial Statistics, the World Bank's World Development Indicators, the Federal Reserve Bank of Saint Louis, and CEIC. Second, the data include three variables forming the proxy for political instability,

All rights reserved. Copyright © 2019 by the IAEE.

notably the Corruption Index, Military Expenses, and Terrorism Index. The Corruption Perceptions Index, published by Trading Economics, ranks countries based on how corrupt their public sector is perceived to be. A country's score indicates the level of public sector corruption on a scale of 0 (highly corrupt) to 100 (very clean). As of July 2019, the Corruption Index for Bahrain is 36, for the U.S. is 71, and for the U.K. is 80.

Military Expenditure is presented in millions of U.S. dollars. Bahrain's Military Expenditure is 1,357 USD million in 2018, compared to 633,565 USD million for the U.S., and 46,883 USD million for the U.K. The Global Terrorism Index measures the direct and indirect impact of terrorism, including its effects on lives lost, injuries, property damage, and the psychological after effects. The score ranks countries according to the impact of terrorism, with 0 implying no impact to 10 implying the highest impact. The current Terrorism Index for Bahrain is 3.88, for the U.S. is 6.07, and for the U.K. is 5.61.

The daily oil prices are extracted from the statistics portal of the OPEC website. The data shows that until the year 2007, Bahrain had the highest oil exports to GDP ratio. After that, the U.S. became a greater oil producer, but still imports a large amount of oil. The U.K.'s situation worsened through the years and the country became a net importer of petroleum products in 2013. In our sample, Bahrain is the only country that has persistently positive net exports of oil products (See Appendix E for data.)

### 4.2 Estimation Methodology

The model is written in terms of equity process $X(t)$:

$$d[X(t)] = X(t)*\{[(1+f(t))*A(Z(t)) - f(t)*i(t) - C]*dt + (1+f(t))*B(Z(t))*d[W(t)] + (1+f(t))*d[M(t)]\}$$

Where $(Z(t))$ is a set of predictors; $M(t)$ is a compound counting process, i.e. $d[M(t)] = U(t)*d[N(t)]$, $N(t)$ is a counting process with intensity $\lambda(t) = \Lambda(Z(t))$, referred to as jump intensity, conditional on $\lambda$, $N(t)$ is independent. Furthermore, $U(t)$ is a random variable, referred to as jump size. As we can see, $X(t)$ is a jump-diffusion, defined in continuous time; however, we observe the process in discrete time. The values of $X(t)$ and other relevant variables are only known at the end of business days; therefore, the estimation problem falls into the framework of time series analysis. Also, we find it easier to work directly with process $Y(t)$:

$$Y(t) = \frac{d[X(t)]}{X(t)} + (f(t)*i(t) + C)*\frac{dt}{(1+f(t))} = A(Z(t))dt + B(Z(t))d[W(t)] + d[M(t)] \tag{5}$$

This way, stochastic processes $a(t) = A(Z(t))$, $b(t) = B(Z(t))$, and $M(t)$ have clear meaning as the drift, volatility, and jump component respectively. Since the data are daily, we chose one day as the time unit and equation (5) becomes:

$$Y(t) = \frac{[X(t+1) - X(t)]}{X(t)} + \frac{f(t)*i_d(t) + C_d}{1+f(t)} = a(t) + b(t)*\varepsilon(t) + M(t+1) - M(t) \tag{6}$$

Where $i_d(t)$ is the daily interest rate, $C_d$ are the daily expenses, $\varepsilon(t)$ is a standard normal variable, independent of everything else, $Y(t)$ equals $U(t)$ with probability $\lambda(t)$ and 0 otherwise. Equation (6) is fairly general. In the rest of the paper and analysis we focus on a subcase, where

Copyright © 2019 by the IAEE. All rights reserved.

$$U(t) = B(t) * U'(t) \tag{7}$$

And $U'(t)$ is a random variable with the distribution constant over time ($U'(t)$ is a stationary process). Equation (6) becomes:

$$Y(t) = a(t) + b(t) * [\varepsilon(t) + 1_{\{N(t+1)-N(t)=1\}} * U'(t)] \tag{8}$$

We view the expression $[\varepsilon(t) + 1_{\{N(t+1)-N(t)=1\}} * U'(t)]$ as a "generalized" residual, with non-trivial, fat-tailed distribution; most of the analytical effort here is directed to capturing these tails. The effort is simplified by the assumption of Equation (7), because now the problems of estimating volatility $b(t)$ and jump component $[1_{\{N(t+1)-N(t)=1\}} * U'(t)]$ are largely decoupled. To help the estimation procedure with numerical stability, we estimate equation (8) for standardized versions of dependent variable $Y(t)$ and predictors $Z(t)$. Formally speaking, we define: $Y_s(t) = \dfrac{[Y(t) - sample\ mean\ (Y(t))]}{sample\ standard\ deviation\ (Y(t))}$.

$$Z_{j,s}(t) = \frac{[Z_j(t) - sample\ mean\ (Z_j(t))]}{sample\ standard\ deviation\ \ (Z_j(t))}$$

and we estimate equation $Y_s(t)$ as:

$$Y_s(t) = a_s(t) + b_s(t) * [\varepsilon(t) + 1_{\{N(t+1)-N(t)=1\}} * U'(t)] \tag{9}$$

where $a_s(t) = A_s(Z_s(t))$, $b_s(t) = B_s(Z_s(t))$, $Z_s(t) = (Z_{1,s}(t), \ldots, Z_{j,s}(t), \ldots, Z_{p,s}(t))$

We note here that $a(t) = a_s(t) * sample\ standard\ deviation\ (Y(t)) + constant$; and $b(t) = b_s(t) * sample\ standard\ deviation\ (Y(t))$.

As is, the model has four distinct components: drift ($a_s$), volatility ($b_s$), jump intensity ($\lambda$), and jump size ($U'$). Generally speaking, each of them should be modeled using different methods. The modeling framework allows for a specification of particular components, semi-parametrically, or even fully non-parametrically. For example, using kernel smoothing provides utility for modeling jump intensity and/or jump size. Still, in this paper, we only use the fully parametric approach; the non-parametric choices are delegated to future work.

Even in the parametric framework, the model is large. We are unable to use maximum likelihood estimation (MLE) which will possibly run numerical instabilities. MLE would be forced to find a local/global maximum in a 10+ dimensional space and standard errors from the estimation might not be reliable. On the other hand, bootstrap or cross-validation would not be suitable because the jump intensity and the distribution of jumps are dynamic. However, it's crucial to note that even though the model is large, it is naturally split into four relatively separate components. For that reason, MCMC was chosen as the method of estimation. In such estimation procedure, we enforce a prior distribution on each set of parameters. Then the parameters for each of the four components are simulated out of their posterior distribution, conditional on the current values of the parameters in the remaining three components.

To fight serial correlation in the simulated values of each coefficient $C_i$, we average the values over small, non-overlapping blocks of iterations. The presence of serial correlation is tested using the autocorrelation function and partial autocorrelation function, which are run on the averaged simulated values of $C_i$. The convergence of the Markov chain is tested using Kolmogorov-Smirnov tests. We run one test for each coefficient $C_i$ every fixed number of iterations. We utilize the "average" rule, where we require that fewer than 5% of p-values be lower than 5%. This accounts for

All rights reserved. Copyright © 2019 by the IAEE.

occurrences of type I error. We also exploit trace plots for informal monitoring of potential convergence for each coefficient.

In this paper, the Fisher's diagnostics is estimated using the Kolmogorov-Smirnov test and calculation of the skewness. Within each modeling specification, we identify the "optimal model" among numerous candidate models. This is based on numerical stability of estimation and statistical significance of coefficients. Next, among various modeling specifications, we identify the "optimal" one, and its results are presented and discussed in the next sub-section. This is based on numerical stability of estimation and Fisher's diagnostics.

### 4.3 Empirical Results

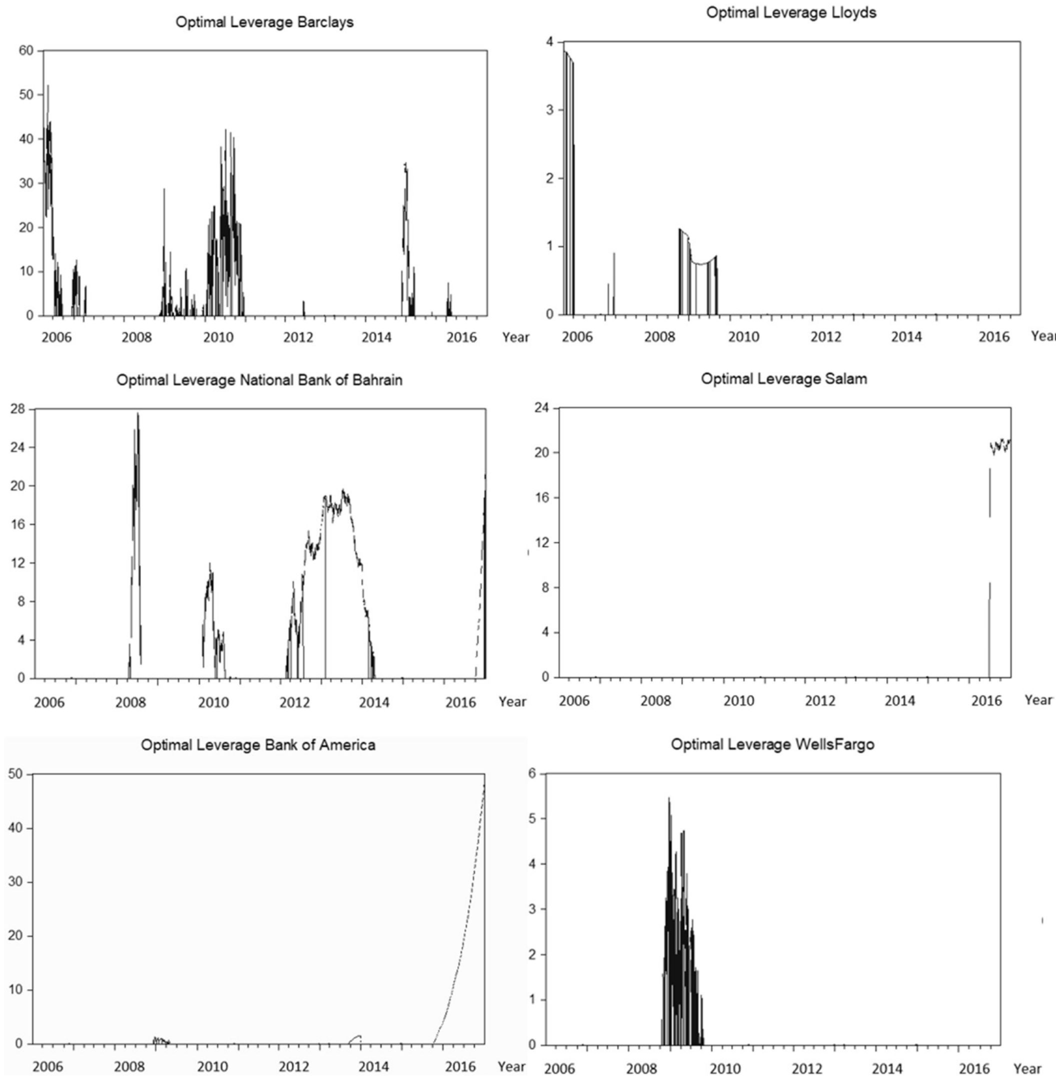
The aim of this study is to examine the behavior of the optimal debt of the sample of six banks, while embedding oil prices and political instability in the model. As mentioned, the main focus is to capture stochastic volatility and jumps jointly. There is ample evidence to support the notion that swings in oil prices and political instability affect the returns of banks through an increase in volatility. Generally speaking, the estimation shows some significant and useful results that are obtained for optimal leverage and the predictors; however, substantial instability of optimal leverage over time is observed. First, the optimal leverage graphs are depicted and analyzed for each bank, and then the predictors' results are presented and analyzed.

Based on the graphs in Figure 1, we can see more distinct results for the oil-exporting countries, mainly Bahrain, followed by the United States, than for the oil-importing United Kingdom. We clearly see that Bahraini banks have high elasticity of bank debt capacities to oil prices, indicating high reliance on oil with low diversification for other sectors. We see declines in optimal debt during the two major oil price falls that occurred during the sample period; the first in the second half of 2008 and the second in late 2014. Optimal debt seems low in 2011, which coincides with the Arab Spring. A decline in oil price results in a decline in bank profitability and investment capacities. Hence, periods of high oil prices are accompanied with periods of high optimal debt, while a collapse in oil prices adversely affects the borrowing capacities in an oil-dependent country such as Bahrain, due to significant collateral squeeze. On the other hand, for oil-importing countries, a fall in oil prices is good news. As the graphs of the United Kingdom above show, in 2006, the second half of 2008, and in late 2014, where there are negative oil price shocks, optimal debt is pretty high. Lower oil prices help reduce the energy cost in production and the cost of living, implying lower inflation rate, which increases households' savings, that in turn is likely to increase their investment. This, in turn, increases the banks' optimal debt level as deposits increase, and therefore lending increases. For the remaining years, although we see that the optimal debt is still somehow related to oil price swings, we see less distinct results. This may reflect a lower elasticity of good investment opportunities to oil prices, which eventually does not negatively affect credit demand similar to Bahrain.

More specifically, of the six banks, the modeling framework was most effective for Barclays and Wells Fargo, followed by Lloyds and National Bank of Bahrain. For each of the six banks, the optimal leverage fluctuated from one day to another. This occurred because optimal leverage is a highly sensitive function of the drift, volatility, and jump intensity. Volatility may change substantially from one day to another. Therefore, if a bank is permitted to rebalance its debt each day, it results in a quite unrealistic trading behavior; however, in reality, leveraging and deleveraging decisions take much longer than a few days to implement.

Copyright © 2019 by the IAEE. All rights reserved.

**Figure 1: Optimal leverage from estimated model for six banks**




*Source:* author's calculation

The optimal leverage for Barclays was extremely high before 2006 and decreased to zero until 2008, when it again started to increase in 2009. In 2010, the optimal debt reached its highest after the crisis, but this peak was followed by a decline in 2011. It remained stable until 2016 with some increases in 2014. For Lloyds, the movement was similar to Barclays in terms of high optimal debt levels before the crisis; however, the optimal debt reached zero around 2009 and maintained that level until the end of the period examined. It should be noted that Lloyds, following its merger with the Trustee Savings Bank, has taken the market lead, which increased the bank's efficiency and performance and consequently the bank's debt ratio.

For National Bank of Bahrain, the results were somewhat different, and the highest optimal debt was in 2008. This is correlated with the shock in oil prices in 2008, especially because Bahrain is a strong oil-exporting country and its economy is highly dependent on oil and gas. High optimal debt levels were also observed between 2012 and 2014, which was when the economy began to

All rights reserved. Copyright © 2019 by the IAEE.

recover from the global crisis. Salam Bank was the only Islamic bank in the sample, and the data exhibited optimal debt levels near zero with the exception of 2016.

The model is not perfectly explanatory for Bank of America. However, some insignificant increases in 2008 and 2013 were observed, which also coincided with the increase in oil prices. It should be noted that the bank had acquired two troubled banks, namely Merrill Lynch and Country-wide, which had a large number of defaulted loans. This probably decreased its optimal debt level; then, the bank exhibited an astronomic increase in optimal debt in 2015 that continued throughout 2016. Wells Fargo showed a low optimal debt level before and during the crisis. The level increased beginning in 2009 and continued until 2010. After 2010, the optimal level remained low throughout the period examined. This decline in debt ratio could be related to the volatile swings in asset prices which lowered the investors' trust, as well as to the overall decline of interest rates due to monetary policy actions.

The estimation output and the graphs related to the estimation of drift, volatility, and jump intensity are presented in Appendix F. Briefly, most of the banks had an increase in drift, volatility, and jump intensity between 2007 and 2009. A decrease was observed in 2009, due to the recovery from the crisis. For the Bahraini banks, an increase between 2011 and 2012 was observed, which occurred due to the global financial crisis, as well as the Arab Spring. The jumps discussed are both in returns and in volatility. The jumps in returns generate large sudden movements, such as the 2008 crash, and for these movements to occur, an extremely high level of volatility needs to occur. The jumps in volatility lead to fast changes in the level of volatility and a lasting effect on the distribution of stock returns. Table 1 below presents the signs of the statistically significant results for the predictors of oil prices and political instability for each country, respectively.

**Table 1: statistically significant results for the predictors of oil prices and political instability**

| | Bahrain | | | U.S. | | | U.K. | | |
|---|---|---|---|---|---|---|---|---|---|
| | Drift | Volatility | Jump Intensity | Drift | Volatility | Jump Intensity | Drift | Volatility | Jump Intensity |
| Corruption | + | + | NA | + | + | – | + | – | – |
| Terrorism | + | + | + | + | + | – | + | NA | + |
| Oil Price | + | – | – | NA | NA | – | – | NA | – |
| Military Expenses | – | – | + | – | – | + | – | + | + |

There were several statistically significant results for the predictors of oil prices and political instability. For example, corruption and terrorism had a positive effect on the drift for five of six banks, while oil prices had a negative effect on drift for three banks. This shows that the mean reverting drift was exerting downward pressure on volatility throughout this period, which was reflected in higher effect of corruption and terrorism on optimal debt ratios and portfolio prices. Military expenditures had a positive effect on the intensity of jumps for all six banks, while oil prices had a negative effect for four banks. In terms of countries, we can see that corruption had a positive effect on the drift for all countries, while it had a positive effect on the volatility for Bahrain and the U.S. only. This is an expected result since the U.K. has the lowest corruption ranking among the 3 countries; the same applies to terrorism.

More specifically, for Barclays, the statistically significant relationship was positive for the drift with corruption and terrorism, and negative for oil and military expenses. For the jump intensity, the relationship was positive with military expenses and negative with corruption. Since the jumps in returns represent the large movements in returns, the positive relationship with military expenses shows the importance of the role played by additional military expenses. Corruption, on the other

Copyright © 2019 by the IAEE. All rights reserved.

hand, does not seem to play a significant role for all banks, probably since the three countries in context are ranked low to moderate on corruption, and the level has been stable for over a decade. As for oil prices, we can see a statistically significant negative sign for the three countries for volatility and jump intensity. Yet, for the drift there is a difference between the oil-exporting country Bahrain and the U.S. and U.K. as oil-importing countries. This aligns with our previous discussion and the assumption that in oil-producing and exporting countries, high oil prices produce expected revenues from credit and higher returns for banks, as well as GDP and credit growth, and that an oil price boom coincides with a credit boom, which drives asset prices up. For Lloyds, the statistically significant relationship for volatility was positive with military expenses and negative with corruption. For jump intensity, the relationship was positive for terrorism and military expenses and negative with oil and corruption. For Bank of America, the statistically significant relationship for volatility was positive with corruption and terrorism and negative with military expenses. For jump intensity, the relationship was positive with military expenses and negative with oil, corruption, and terrorism. For Wells Fargo, corruption and terrorism had a positive, statistically significant relationship with drift, and military expenses had a negative relationship. On the other hand, military expenses had a positive relationship with jump intensity, while oil price, corruption, and terrorism had a negative one. For National Bank of Bahrain, the statistically significant relationships with predictors are as follows: positive for drift with oil price, political corruption, and terrorism and negative with military expenses. For volatility, terrorism was positively related, while military expenses were negatively related. Military expenses were also significantly related to jump intensity. A bit of a deviating behavior seems to be visible at Salam Bank of Bahrain which had a statistically significant positive relationship for drift and volatility with corruption, positive as well for drift and jump intensity with terrorism, and finally, positive with military expenses for volatility and jump intensity. Oil price showed a negative relation to the three terms. This does not come as a surprise, since Salam Bank, as opposed to National Bank of Bahrain, is not owned nor subsidized by the government. Hence, the bank's investment portfolio is much more diversified and less reliant on oil production.

Overall, though our sample is small, relying only on data sets of a small number of banks of either oil-exporting or oil-importing countries, the impact of our chosen drivers of drift, volatility and jump intensity is quite different for the two types of countries. We thus have to characterize our results as roughly in line with what one expects from our proposed model, but more data is needed for further research to obtain more distinct results.

### 4.4 Policy Implications

With respect to our main endeavor, the empirical regularity of a positive association between optimal leverage and oil price shocks, leads to the facile conclusion that an increase in lending appears to be safe when oil prices are high; yet, increased risk of default can rise through increased lending. So, what is it that policymakers need to consider? The main policy implication for all countries is to reduce overall risky debt, and develop an optimal debt structure which needs to be followed in order to avoid the risk of financial instability and default. The first challenge in designing an effective policy to make optimal debt a fixed ratio based on the net worth of a financial corporation, is a regulatory one. High risk implies high return, therefore, decreasing the risk by providing secured lending will be a challenging task. We have seen that a risky portfolio that is driven by commodity prices, such as oil prices, props up the lending to dangerous levels. We have tried to distinguish between optimal and actual leveraging of financial institutions. We could observe that what has been called optimal debt is even rising with the oil price spikes, and so is the

All rights reserved. Copyright © 2019 by the IAEE.

actual level of debt. A further policy challenge is to introduce and strengthen risk weighted capital buffers and the use of collaterals that can quickly turn into liquidity. Collaterals are a powerful tool of stability, despite the repossession cost they impose on the banks. Policymakers should impose higher collaterals on riskier borrowers, and also for financial institutions exposed to such shocks as oil price shocks. In addition, monetary policy that increases the interest rate will prompt a greater collateral, closer to optimal leverage level, which affects borrower's investments' opportunities and risks, hence its effect on the bank's portfolio risk and choice. Thus, policymakers should also be aware that the value of collaterals are also endogenously determined, for example based on the level and volatility of the oil price.

This research has some more general implications for regulations as well. It shows the risk associated with leverage, triggered by portfolio value, and the hereby generated vulnerability of banks, and therefore the need for proper regulations that protect the banking system. Also, network analysis today illustrates the necessity of understanding the way in which institutions are linked and affect one another. A prime example is Lehman Brothers' insolvency. This event rippled then into the money market mutual fund sector, causing widespread withdrawals from money market mutual funds, which then forced the government to rescue the financial sector from failing. Yet, after the debacle, confidence in this sector plummeted, which subsequently caused a severe melt-down of the global economy. Much literature has studied those events and the consequence for new regulatory tasks as attempted in the U.S. Dodd-Frank Act.

## 5. CONCLUSION

This paper presents a theoretical model that extends Stein's (2012) model of optimal leverage to a model that not only describes portfolio fluctuations using a single measure of volatility, but also exhibits an added jump-diffusion component that captures the jump size and intensity of oil prices and political instability predictors. The optimal debt derived was estimated empirically for a sample of six banks using a data set with three levels of aggregation: bank, country, and supra-national levels. Oil prices and political instability were of primary importance in this model.

The results showed that there were similarities between the six banks in terms of oil prices and political instability with jump intensity, though the effects on drift, volatility and jump intensity appeared to be distinct. As to the policy shock variables, political corruption and terrorism had a positive effect on drift for five of the six banks, while military expenses had a positive effect on the intensity of jumps for all six banks. Oil price had a negative effect on drift and jump intensity for four banks in the U.S. and the U.K., while exhibiting a different drift effect for the oil-exporting country, Bahrain. Regarding optimal leverage, the results of the estimated model showed that there was a dissimilarity between inferences made for the different banks. Generally speaking, both banks in the U.K. exhibited high optimal debt before the financial crisis of 2007–2009. For Bahrain, almost throughout the period examined, the optimal debt was high for the conventional bank, while it was low for the Islamic bank. Finally, for the U.S., Wells Fargo had a higher optimal debt than Bank of America. Several years prior to the crisis, Bank of America's optimal debt ratio was low, at the same time when the bank's acquisitions of both Merrill Lynch and Countrywide Financial in 2008 took place. Bank of America's asset prices started to rise in 2011, thus improving the bank's actual debt ratio, while Wells Fargo had constant swings in asset prices, which led to the decline of the actual debt ratio.

The optimal debt ratio estimation presented in this paper is an important measure that can help banks detect a sustainable debt level above which it becomes risky to leverage. This is a key

Copyright © 2019 by the IAEE. All rights reserved.

financial metric in that it allows banks to avoid instability and/or risk of insolvency when they take this metric seriously. However, banks do not accurately assess optimal debt, and in most cases, when the optimal debt moves down, excess leverage increases for a given level of actual leverage.

We add to the previously referenced academic studies the role of rapid changes of oil prices and political stability, and their impact on the stability of the banking system. We use the oil price change as an example of a rare but large event, and model it as the jump-diffusion process with its impact on banks' portfolios, their asset prices, and balance sheets. Here, too, the banks' vulnerability and exposure to insolvency risk can become an important threat to macroeconomic stability and performance. Given our results for the jump-diffusion component built into the Stein model of optimal bank debt, we could also spell out some further policy implications with further increase of sample size.

## REFERENCES


Baffes, J., M.A. Kose, F. Ohnsorge, and M. Stocker (2015). "The great plunge in oil prices: Causes, consequences, and policy responses." *Consequences, and Policy Responses*. https://doi.org/10.2139/ssrn.2624398.

Bates, D. (1996). "Jumps and Stochastic Volatility: Exchange Rate Processes Implicit in Deutsche Mark Options." *Review of Financial Studies* 9(1): 69–107. https://doi.org/10.1093/rfs/9.1.69.

Berg, B.A. (2004). *Markov chain Monte Carlo simulations and their statistical analysis: with web-based Fortran code*. World Scientific Publishing Company. https://doi.org/10.1142/5602.

Berg, B.A. (2005). "Introduction to Markov chain Monte Carlo simulations and their statistical analysis." Markov Chain Monte Carlo Lect Notes Ser Inst Math Sci Natl Univ Singap 7: 1–52. https://doi.org/10.1142/9789812700919_0001.

Brémaud, P. (1981). *Point processes and queues: martingale dynamics (Vol. 50)*. New York: Springer-Verlag. https://doi.org/10.1007/978-1-4684-9477-8.

Brooks, S., A. Gelman, G. Jones, and X.L. Meng (Eds.) (2011). *Handbook of Markov Chain Monte Carlo*. CRC press. https://doi.org/10.1201/b10905.

Brunnermeier, M.K. (2009). "Deciphering the liquidity and credit crunch 2007–2008." *Journal of Economic perspectives* 23(1): 77–100. https://doi.org/10.1257/jep.23.1.77.

Brunnermeier, M.K. and Y. Sannikov (2014). "A macroeconomic model with a financial sector." *American Economic Review* 104(2): 379–421. https://doi.org/10.1257/aer.104.2.379.

Burbidge, J. and A. Harrison (1984). "Testing for the effects of oil-price rises using vector autoregressions." *International Economic Review* 459–484. https://doi.org/10.2307/2526209.

Darby, M.R. (1982). "The price of oil and world inflation and recession." *The American Economic Review* 72(4): 738–751.

Eberhardt, M. and A. Presbitero (2018). "Commodity Price Movements and Banking Crises." IMF Working paper. https://doi.org/10.5089/9781484366776.001.

Ftiti, Z., S. Kablan, and K. Guesmi (2016). "What can we learn about commodity and credit cycles? Evidence from African commodity-exporting countries." *Energy Economics* 60: 313–324. https://doi.org/10.1016/j.eneco.2016.10.011.

Gilje, E.P. (2017). "Does local access to finance matter? Evidence from U.S. oil and natural gas shale booms." *Management Science*.

Gilks, W.R., S. Richardson, and D. Spiegelhalter (Eds.) (1995). *Markov chain Monte Carlo in practice*. CRC press. https://doi.org/10.1201/b14835.

Gross, M., J. Henry, and W. Semmler (2017). "Destabilizing effects of bank overleveraging on real activity-An analysis based on a threshold MCS-GVAR." *Macroeconomic Dynamics* 1–19. https://doi.org/10.1017/S1365100516001024.

Hamilton, J.D. (1996). "This is what happened to the oil price-macroeconomy relationship." *Journal of Monetary Economics* 38(2): 215–220. https://doi.org/10.1016/S0304-3932(96)01282-2.

Hamilton, J.D. (2008). *Oil and the macroeconomy, The new Palgrave Dictionary of Economics*. Blume (second ed.), Palgrave Macmillan. https://doi.org/10.1057/978-1-349-95121-5_2119-1.

Hamilton, J.D. (2011). "Historical oil shocks." (No. w16790). National Bureau of Economic Research. https://doi.org/10.3386/w16790.

Harrison, B. and W. Moore (2012). "Stock market efficiency, non-linearity, thin trading, and asymmetric information in MENA stock markets." *Economic Issues* 17(1): 77–93.


All rights reserved. Copyright © 2019 by the IAEE.

Hilliard, J.E. and J.A. Reis (1999). "Jump processes in commodity futures prices and options pricing." *American Journal of Agricultural Economics* 81(2): 273–286. https://doi.org/10.2307/1244581.

Jones, P.W. and P. Smith (2009). *Stochastic processes: an introduction*. Chapman and Hall/CRC.

Kablan, S., Z. Ftiti, and K. Guesmi (2017). "Commodity Price Cycles and Financial Pressures in African Commodities Exporters." *Emerging Markets Review* 30: 215–231. https://doi.org/10.1016/j.ememar.2016.05.005.

Khandelwal, P., M.K. Miyajima, and M.A.O. Santos (2016). *The impact of oil prices on the banking system in the GCC*. International Monetary Fund. https://doi.org/10.5089/9781475523393.001.

Kilian, L. (2014). "Oil price shocks: Causes and consequences." *Annu. Rev. Resour. Econ.* 6(1): 133–154. https://doi.org/10.1146/annurev-resource-083013-114701.

Lai, T.L. and H. Xing (2008). *Statistical models and methods for financial markets*. New York: Springer. https://doi.org/10.1007/978-0-387-77827-3.

Lawler, G.F. (1995). *Introduction to Stochastic Processes*. Chapman & Hall/CRC.

Merton, R.C. (1976). "Option pricing when underlying stock returns are discontinuous." *Journal of financial economics* 3(1–2): 125–144. https://doi.org/10.1016/0304-405X(76)90022-2.

Mittnik, S. and W. Semmler (2012a). "Regime Dependence of the Multiplier." *Journal of Economic Behavior and Organization* 83(3): 502–52. https://doi.org/10.1016/j.jebo.2012.02.005.

Mittnik, S. and W. Semmler (2011). "The instability of the banking sector and macrodynamics: Theory and empirics." *Social Science Research Network*. http://dx. doi. org/10.2139/ssrn, 1871043. forthcoming Macroeconomic Dynamics, 2018.

Mittnik, S. and W. Semmler (2012). "Regime dependence of the fiscal multiplier." *Journal of Economic Behavior & Organization* 83(3): 502–522. https://doi.org/10.1016/j.jebo.2012.02.005.

Protter, P.E. (2005). "Stochastic differential equations." In *Stochastic integration and differential equations*. Springer, Berlin, Heidelberg. (pp. 249–361). https://doi.org/10.1007/978-3-662-10061-5_6.

Robert, C.P., G. Casella, and G. Casella (2010). *Introducing Monte Carlo methods with r* (Vol. 18). New York: Springer. https://doi.org/10.1007/978-1-4419-1576-4.

Ross, S.M. (1995). *Stochastic Processes* (2nd Ed). New York: Wiley.

Schleer, F. and W. Semmler (2016). "Banking Overleveraging and Macro Instability: A Model and VSTAR Estimations." *Jahrbücher für Nationalökonomie und Statistik* 236(6): 609–638. https://doi.org/10.1515/jbnst-2015-1042.

Schleer, F., W. Semmler, and J. Illner (2014). "Overleveraging in the Banking Sector: Evidence from Europe." ZEW working paper. https://doi.org/10.2139/ssrn.2503838.

Semmler, W. and D. Parker (2017). "Asset Accumulation with Heterogeneous Households: The Rise of Wealth Disparity." In *Inequality and Finance in Macrodynamics*. Springer, Cham. (pp. 243–270). https://doi.org/10.1007/978-3-319-54690-2_11.

Stein, J.L. (2012). *Stochastic Optimal Control and the U.S. Financial Debt Crisis*. New York: Springer. https://doi.org/10.1007/978-1-4614-3079-7.

Stein, J.L. (2012). "The diversity of debt crises in Europe." In *Stochastic Optimal Control and the U.S. Financial Debt Crisis.* Springer, Boston, MA. (pp. 133–154). https://doi.org/10.1007/978-1-4614-3079-7_8.

Copyright © 2019 by the IAEE. All rights reserved.

IAEE INTERNATIONAL ASSOCIATION *for* ENERGY ECONOMICS
WWW.IAEE.ORG

The IAEE is pleased to announce that our leading publications exhibited strong performances in the latest 2018 Impact Factors as reported by Clarivate. The Energy Journal achieved an Impact Factor of 2.456 while Economics of Energy & Environmental Policy saw an increase to 2.034.

Both publications have earned SCIMago Journal Ratings in the top quartile for Economics and Econometrics publications.

IAEE wishes to congratulate and thank all those involved including authors, editors, peer-reviewers, the editorial boards of both publications, and to you, our readers and researchers, for your invaluable contributions in making 2018 a strong year. We count on your continued support and future submission of papers to these leading publications.