An Examination of The Stability of Bank Betas During Extreme Market Volatility: The Case ff The Financial Crisis and The Pandemic

John S. Walker [a], Victoria Geyfman [b] and Necati Tekatli [c]
[a,c] Kutztown University of Pennsylvania, USA
[b] Bloomsburg University of Pennsylvania, USA

We examine the time-varying nature of bank beta coefficients during periods of extreme market volatility. Specifically, we observe a rise in betas during the global financial crisis of 2007–2009 and the current Covid-19 pandemic, when using two common bank indices and the S&P 500 index as proxies for systematic risk. Periods of volatile market conditions offer a test of diversification and whether or not market betas are stable over time. This study highlights shortcomings of the standard ordinary least squares estimation of market betas used in the capital asset pricing model. We apply more rigorous econometric-based techniques, including Kalman filtering, to examine the stability of beta coefficients and to detect structural breaks during periods of extreme market volatility. This analysis should be of interest to academicians, consultants, and bank practitioners who are trying to estimate accurate market betas for cost of capital calculations and fair market valuations of bank stocks.

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1. Introduction

Financial managers know that if they produce returns that exceed the firm's cost of capital, they are creating value for their shareholders. Conversely, if their returns fall short, they are destroying value. For banks, and particularly for smaller community banks (those banks with assets below $10 billion that concentrate on providing traditional banking services to the local communities), the focus should be specifically on the cost of *equity* capital. The reason is that equity capital usually constitutes the largest part of smaller banks' capital structure; plus, it is tougher to estimate its cost than the debt component. Damodaran (2013) observes that "capital at financial services firms seems to be more narrowly defined as including only equity capital."

One of the main objectives of today's bank managers is to create value for shareholders; without this focus, a bank may find itself with lackluster profitability and potentially a target for takeover. While we recognize that all stakeholders—including customers and regulators—remain important, we assert that bank managers have grown more focused on the bottom line. It is likely that the shift in focus to bottom-line performance has partly been brought on by activist investors. Moreover, this pursuit of building value for shareholders helps explain the consolidation of the bank sector during the past two decades. In 1999, there were 10,222 FDIC-insured banks, while today there are roughly half as many at 5,116 banks (FDIC, 2020).

When estimating a bank's cost of capital, industry practitioners often utilize the capital asset pricing model (CAPM) to calculate the cost of the equity component. While those in the finance profession have identified shortcomings of the CAPM, the reality is that it is used heavily in industry to arrive at an estimate for the cost of equity (Brotherson et al., 2013). To utilize the CAPM, estimates for the market risk premium and a stock's beta are needed. The beta for a firm's stock is an indication of its return volatility relative to the overall market; it is the measure of the firm's systematic, non-diversifiable market risk.

Finance theory suggests that the more market risk an investor takes, the higher the expected return should be. Estimates of a stock's beta are based on the return volatility and correlation between the stock's returns and the market's returns over time. Studies have shown that the assumption of a stable correlation is actually a poor one (Brooks et al., 1992; Choudhry, 2002; Choudhry, 2005; Andersen et al., 2006). In fact, research has shown that the correlation across markets increases in a down market, precisely when lower correlations can help an investor (Longin & Solnik, 1995; Longin & Solnik, 2001; Goetzmann et al., 2001). If correlations within an investor's portfolio increase during a down market, the risk of losses will rise. In other words, correlations that increase during down markets curtail the benefits of diversification.

In our initial research, detailed later in the results section, we found that during the current pandemic period, the volatility of the S&P 500 Index jumped over 500%, while the volatility of the banking sector indices spiked by more than 400%. Correspondingly, the correlation between banking institutions and the market went from between 0.68 (for NASDAQ banks) to 0.76 (for KBW NASDAQ banks) all the way up to a range of 0.95 to 0.97. From an investor's perspective, the diversification benefits seemingly disappeared just when the market turbulence surged, which was bad timing for an investor. The shift in correlation in turn produced higher betas, suggesting more market risk. Similar findings were observed during the financial crisis of 2007–2009, where we again found a shift in betas when market volatility elevated. Our preliminary findings prompted a more in-depth examination of the stability of bank betas during the last two periods of unusually high market volatility—the financial crisis and the current pandemic period. This study uses progressively more robust statistical and econometric techniques to gather evidence as to what is happening to bank betas when volatility spikes. We discuss the implications for bank managers who are striving to build value for shareholders and remain independent.

This study contributes to the body of research that analyzes time-varying betas. This research should be of interest to those in the banking industry who need to estimate accurate market betas for cost of capital calculations and fair market valuations of bank stocks. Using data for the pre- and post-financial crisis period (2004 through 2012) and the pre- and current Covid-19 pandemic period (2015 through March of 2020), this study compares the results derived from traditional ordinary least squares technique (OLS) to those found from the rolling-window ordinary least squares methodology (RW-OLS) and a more robust time-varying coefficient estimation method that incorporates Kalman filtering (TVC-KF).

The paper is organized as follows. Section 2 contains a literature review that addresses the shortcomings of the traditional beta approach and discusses how time-varying beta coefficients can produce a more reliable estimate of the cost of capital for banks. Then Section 3 outlines the three estimation techniques used to perform time-varying analysis and describes the data used in the estimation procedures. Section 4 presents our results. And finally, in Section 5 we discuss our findings and explain the implications for investors and bank managers.

2. Literature Review

The CAPM is one of the most researched models in finance. An estimate for the systematic risk component—namely, the beta coefficient, is an essential metric for security analysis and company valuation. The accuracy and reliability of the beta is critical in the valuation of equity securities and in determining investment strategies. It is typically assumed that beta is time invariant, but many researchers find that using a fixed beta in the CAPM fails to explain the dynamic volatility of markets (Bos & Newbold, 1984; Collins et al., 1987; Brooks et al., 1992; and Choudhry, 2002, 2005). Adrian and Franzoni (2005) show that models without time-varying betas fail to capture the cross-sectional variations in returns and dynamics in market volatilities, which can lead to inaccurate estimates of the underlying beta and, thus, biased estimates of the cost of capital.

To address this criticism, Campbell and Vuolteenaho (2004), Fama and French (2005), Petkova and Zhang (2005), Lewellen and Nagel (2006), and Ang and Chen (2007) proposed several time-varying beta models to measure the underlying betas and market volatility. Many of these models use granular daily returns to extract information about the current level of volatility and then attempt to forecast the next period's return volatility. Some studies use higher-frequency data to forecast volatility (Andersen et al., 2006). However, these models fail to fully capture the dynamics of volatility, especially when the volatility changes unexpectedly, as can happen during structural changes or market regime switches (Andersen et al., 2006). This study investigates the time-varying betas during the financial crisis of 2007–2009 and the current Covid-19 pandemic when market volatility elevated significantly.

The traditional approach for beta estimations is the OLS regression of the market model form of the CAPM. Because the traditional OLS regression procedure fails to address the dynamic changes in market conditions, some researchers use a rolling-window ordinary least squares (RW-OLS) regression (Berardi et al., 2002). The RW-OLS technique uses various data ranges (either overlapping or nonoverlapping) over the period of 30 days, 12 months, 24 months, or longer (Brooks, 2008). The advantage of using the RW-OLS procedure is that it adjusts more quickly than traditional OLS to the structural changes in the beta coefficient (Faff et al., 2000a; Renzi-Ricci, 2016). A drawback of using the RW-OLS method is that this approach is static *within* the time period window and the choice of the window is arbitrary. A researcher can set a narrower window range, for example, 30 days as opposed to 12 months or 24 months, to react quicker to the structural changes, but that may produce very volatile beta estimates (Tabak & Dunbar, 1999).

Another approach that has been used for beta estimations is the Kalman filter (KF) (Garbade & Rentzler, 1981; Gastaldi & Nardecchia, 2003; Ebner & Neumann, 2005). The main benefit of the KF is its quick reaction to the dynamic changes in the market. The methodology produces more stable beta estimates compared to the RW-OLS method (Faff et al., 2000a; Renzi-Ricci, 2016). Applying the KF is a recursive process that refines the model's estimates over time by incorporating new observations into the estimation process (Wells, 1996). Studies show that using the KF technique produces more robust estimations that have been shown to be superior to several of the GARCH-family models (Zhang & Choudhry, 2017). Furthermore, the results produced by the KF technique are robust across industries (Faff et al., 2000b) and countries (Faff et al., 2000a; Ebner & Neumann, 2005). For example, Faff et al. (2000a) use a large number of sectors in the UK and find that market betas are largely unstable, but become more stable when the data is run through the KF estimation algorithm.

3. Methodology and Data Description

In this study, we evaluate the stability of CAPM betas for the banking sector during periods of extreme market volatility, specifically during the global financial crisis of 2007–2009 and the Covid-19 pandemic. We use three methods to estimate the CAPM beta: the traditional OLS technique, the RW-OLS methodology, and the TVC-KF procedure.

The equity beta is the single factor in the CAPM, which is used to estimate the cost of equity capital. In turn, the cost of equity is incorporated into the calculation of a firm's weighted average cost of capital (WACC). For many smaller banks, the cost of equity (the required rate of return) is a close approximation of their WACC because they typically have little or no long-term debt. To find a stock's beta, which is the response of a stock's return to systematic risk, regression of the market model is often used. There are different forms of the market model found in the literature (Brealey, Myers, & Allen, 2020). In the traditional OLS estimation of the market model, a stock's beta for any one firm is assumed to be constant, unless its capital structure changes. However, researchers have provided abundant evidence leading to the conclusion that this is a poor assumption and that beta is time-variant, consistent with the dynamic nature of financial markets (Bos & Newbold, 1984; Collins et al., 1987;

Brooks et al., 1992; and Choudhry, 2002, 2005). We estimate the CAPM and apply it in a time series context at time t to equation (1):

$$R_{it} = \alpha_{it} + \beta_{it} R_{Mt} + \varepsilon_{it} \quad (1)$$

where R_{it} is the equity market return for the asset i at time t, a_{it} is the intercept, R_{Mt} is the return on the market portfolio, β_{it} measures the systematic risk, and ε_{it} captures the regression residuals, such that $E(\varepsilon_{it})=0$ for all i and t. Unsystematic risk is measured by the variance of the regression residuals from this model.

Then, to capture the anticipated time-variant nature of beta for the bank sector, we next use a RW-OLS regression procedure. This approach typically uses rolling least squares estimation over some window to produce a current estimate of beta, which is then treated as the estimate of beta going forward. RW-OLS involves using a shorter and more recent data window to estimate the regression parameters. We use 90-trading-day rolling windows in the regression (1) above. Discarding past data in this manner allows the model to capture recent market changes more rapidly, but the drawback of the RW-OLS method is the fact that we lose some statistical accuracy because the estimation is performed on a smaller sample (Faff et al., 2000a). Also, the range of the rolling-window is somewhat arbitrary, and an analyst may lose some critical data, depending on the narrowness of the window used.

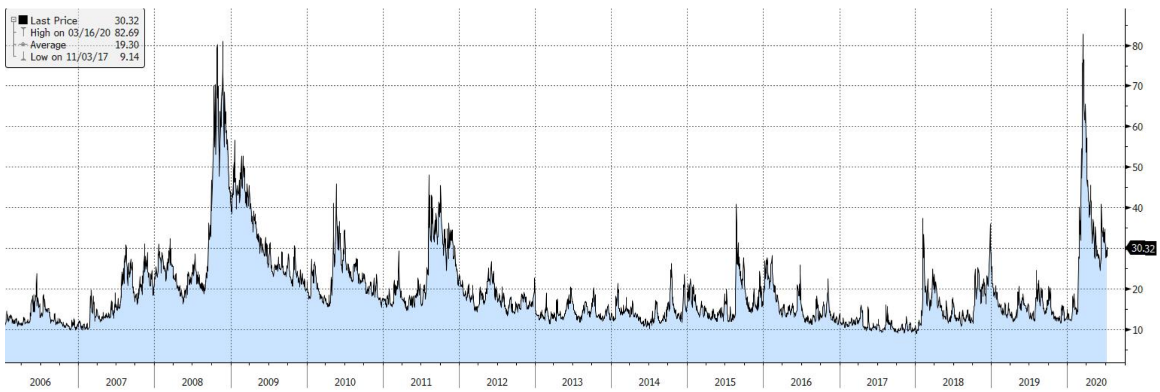
In the third approach, we use the TVC-KF procedure to estimate time-varying (dynamic) coefficients for beta. TVC-KF is a state-space estimation method that includes a recursive algorithm that repeatedly updates the parameter estimates by using the new observed information at each point in time and by measuring a prediction error. The technique has been shown to overcome the limitations of the OLS technique in measuring time-varying betas (Renzi-Ricci, 2016). The procedure consists of two steps. The first step is to run the observation (measurement) market model equation (1) above. In the second step, the parameters are allowed to evolve through the process described by the state (transition) equation:

$$\beta_{it} = T_i \beta_{i,t-1} + \tau_{it} \quad (2)$$

where the parameter T_i captures the relationship between the beta in any given period $t-1$ and the beta in the following period, t. The error term, τ_{it}, is normally distributed and constitutes the random component of the change in the beta. Specifically, the filter starts the procedure with the current estimate of the unknown β_{it} in the transition equation (2) and calculates the best *ex ante* estimate of beta for the following period, $t+1$. This estimate is then used in the market equation (1) to get a prediction for $R_{i,t+1}$ and using the observed market return $R_{M,t+1}$. The process calculates the prediction error defined as the difference between the observed and the predicted equity market return. The algorithm is solved recursively by maximum likelihood estimation (MLE), which minimizes the prediction error.

All the data used in this study were obtained from Bloomberg L. P., S&P Global Market Intelligence, the Federal Reserve Bank of St. Louis, and the FDIC. To assess market conditions, specifically market volatility, we used the CBOE volatility index, abbreviated VIX. Figure 1 shows this so-called "fear index." From 2006 to the present, there are two periods when market volatility jumped significantly: during the 2007–2009 financial crisis and at the start of the Covid-19 pandemic. The VIX index was consistently in the range of 10–30 for the period shown, with three very brief blips up to around 40. The periods of unusually high market volatility seen during the financial crisis and the early stage of the pandemic provide an opportunity to estimate beta during periods of high market volatility and compare it to beta when markets are more settled.

Figure 1: CBOE Volatility Index (VIX)



Source: Bloomberg L.P.

We use two bank indices as proxies for the bank sector—the NASDAQ Bank Index (CBNK) and the KBW Bank Index (BKX). The S&P 500 Index is our proxy for the overall stock market. The NASDAQ Bank Index is a broad-based capitalization-weighted index of domestic and foreign common stocks of banks that are traded on the NASDAQ National Market System (NASDAQ/NMS) as well as Small Cap Market. The index contains securities of NASDAQ-listed companies classified according to the Industry Classification Benchmark as banks. Furthermore, the index includes banks that are providing a broad range of financial services, including retail banking, loans, and money transmissions (NASDAQ Overview, 2020). As for the KBW Bank Index, it is a modified capitalization-weighted index consisting of 24 exchange-listed National Market System stocks, representing large national money center banks, regional banks, and leading regional institutions (NASDAQ Overview, 2020). Finally, the S&P 500 Index is a proxy for the market portfolio. According to Bloomberg, the SPX is regarded as the best single gauge of large-cap US equities and serves as the foundation for a wide range of investment products. The index includes 500 leading companies and accounts for approximately 80% coverage of available market capitalization. Figure 2 plots all three data series from 2007 to 2020.

Figure 2: Two Bank Indices versus the S&P 500

Source: Bloomberg L.P.

*For a more meaningful comparison, S&P and NASDAQ Bank indices are plotted on a different axis than KBW due to a difference in base levels.

Figure 2 shows that during the financial crisis and during the Covid-19 pandemic, the market plummeted. Thus, for example the volatility of the S&P 500 jumped over 500% after February 2020, while the volatility for banks spiked by more than 400%. The jump corresponds to the spike in the VIX. What does it mean for investors? How does it affect the benefits of diversification? The results are considered in the next section.

4. Results

This section evaluates the dynamics of risk exposure and beta coefficients during the financial crisis of 2007–2009 (also termed the Great Recession) and the Covid-19 pandemic of 2020. We first address the stability of the CAPM betas and then show how they evolve overtime, especially during periods of extreme market volatility.

The estimate of a stock's beta depends on return volatilities and the correlation between a stock's returns and market returns over time, as reflected in the following formula:

$$\beta_i = \rho_{im}\, \sigma_i / \sigma_m \tag{3}$$

where ρ_{im} is the correlation coefficient between the returns on the bank portfolio and the market returns, σ_i is the standard deviation of the returns on the bank portfolio, and σ_m is the standard deviation of the market returns. Researchers have shown that the assumption of a stable correlation is actually a poor one (Fabozzi & Francis, 1978; Cheng, 1997). In fact, they showed that the correlation across markets increases in a down market (precisely at the wrong time!), which increases the risk of losses in an investor's portfolio and removes the benefits of diversification.

The turbulent markets brought on by the financial crisis of 2007–2009 and the pandemic of 2020 offer a test of diversification and whether or not betas exhibited time-varying patterns. As shown in Tables 1 and 2, the correlations and betas have increased dramatically during the financial crisis and pandemic. Between 2007 and 2009, the US stock market plummeted. Table 1 presents the evidence of elevated betas during the financial crisis. Note that different banking sub-sectors produce distinctly different increases in their betas, with the large bank sector (KBW) exhibiting greater changes in correlations.

Table 1: Statistics for Before and During the 2007–2009 Financial Crisis

	Bull Market	Bear Market	Change
Correlation: NASDAQ Bank/S&P 500	0.85	0.86	1%
Std. Dev.: S&P 500	0.71%	1.74%	145%
Std. Dev.: NASDAQ Bank	0.83%	2.38%	187%
Beta: NASDAQ Bank/S&P 500	0.99	1.18	19%
Correlation: KBW NASDAQ Bank/S&P 500	0.84	0.81	4%
Std. Dev.: KBW NASDAQ Bank	0.88%	3.62%	311%
Beta: KBW NASDAQ Bank/S&P 500	1.04	1.69	63%

Source: Authors' calculations

Similarly, a little over a decade later, the stock market plummeted again in February 2020. Table 2 presents the evidence of elevated betas during the early stages of the pandemic. The volatility of the S&P 500 increased five-fold, while the volatility of bank returns increased four-fold, with a resultant jump in correlation coefficients.

Table 2: Statistics for Before and During the Pandemic

	Bull Market	Bear Market	Change
Correlation: NASDAQ Bank/S&P 500	0.68	0.95	40%
Std. Dev.: S&P 500	0.84%	5.41%	544%
Std. Dev.: NASDAQ Bank	1.21%	6.56%	442%
Beta: NASDAQ Bank/S&P 500	0.98	1.15	17%
Correlation: KBW NASDAQ Bank/S&P 500	0.76	0.97	28%
Std. Dev.: KBW NASDAQ Bank	1.30%	7.48%	475%
Beta: KBW NASDAQ Bank/S&P 500	1.18	1.34	14%

Source: Authors' calculations

Overall, we observe that markets experienced distinct structural breaks in the CAPM betas during the financial crisis and the pandemic, when the stock market plummeted and betas rose, especially for large money center banks. The Chow test (Chow, 1960) confirms the validity of these results and shows distinct structural breaks on October 7, 2007 and February 19, 2020. The null hypothesis tests the equality of betas before and after the break date. Test results appear in Table 3. Both break dates are statistically significant, which provides evidence of a change in betas during the financial crisis and pandemic.

Table 3: Stability Tests for Betas for Given Break Dates

Financial Crisis Period		
	KBW NASDAQ Bank	NASDAQ Bank
***F* statistic**	9.25*	10.28*
Pandemic Period		
	KBW NASDAQ Bank	NASDAQ Bank
***F* statistic**	32.69*	7.60*

Source: Authors' calculations.

* Results are statistically significant at 1% significance level

Note: The Durbin-Watson and Breusch-Godfrey tests of the CAPM post-estimation results indicated no serial correlation in residuals.

Further, we test the stability of betas during a given period of each global crisis. We assume no specific structural break dates and run the test to determine if the betas are stable over the given period of time. We use the cumulative sum (cusum) of OLS residuals test (Brown et al., 1975; Ploberger & Krämer, 1992). The cusum test assesses the stability of coefficients in a linear regression model, which is based on sums of squares of recursive residuals. The null hypothesis assumes that the coefficients are constant. Values outside an expected range suggest structural break in the model. The cusum test results reported in Table 4 strongly reject the null hypothesis of no structural breaks during the financial crisis and pandemic periods.

Table 4: Beta Stability Tests

Time Period	Number of observations	Test Statistic
April 2004–March 2012	1,925	17.66*
March 2015–March 2020	1,170	12.78*

* Results are statistically significant at 1% significance level.

After verifying that the betas are not stable and entail structural changes during both the financial crisis and the pandemic, we estimate the CAPM using three different methods: the traditional OLS, rolling-window OLS, and the more robust Kalman filtering for the truly dynamic, time-varying parameter estimation. The analysis provides comparisons of the results in Figures 3–6. We also test for statistical robustness of the results.

Figures 3 and 5 present the pairwise comparisons of the entire-period OLS versus the RW-OLS and the TVC-KF approaches for the KBW Bank Index, while Figures 4 and 6 provide the same comparisons for the NASDAQ Bank Index. The results show that the RW-OLS and TVC-KF approaches do a better job than the standard OLS technique in detecting structural breaks in the beta. It is apparent that OLS estimates (BetaOLS) do not change significantly throughout the entire period. Rolling-window estimates (BetaRW) are quite volatile because the RW-OLS method uses information only from a narrow window around the parameter estimates. In contrast, the Kalman filter estimates (BetaKF) are less volatile and more reliable because the TVC-KF method refines the estimates by incorporating the entire observation set from the past and future information, thus smoothing out parameter estimates.

Figures 3 and 4 show that during the global financial crisis both bank indices, the KBW and the NASDAQ Bank Index, had a beta around one, until the market started to fall and the fear index surged. At that time, both stock price volatility and market risk were affected. Interestingly, beta estimates using the KBW Bank Index were higher than those for NASDAQ Bank Index during the financial crisis, perhaps due to the difference in trading activity characteristic of the banks in each index (KBW is comprised of larger financial institutions). However, note that the correlations changed very little as we moved from the bull market into the bear market period; instead, the increase in betas was attributed to the relative volatility of bank returns compared to the S&P 500. Betas reached their peak values between 2.0 and 2.5 for the KBW Bank Index and 1.4 and 1.5 for the NASDAQ Bank Index between July 2008 and October 2008 (recall that Lehman Brothers collapsed on September 15, 2008). During the same period, the VIX experienced more than a three-fold increase from 20s to 70s, confirming that higher market volatility is associated with higher bank betas for this period. Following the myriad of stabilization efforts by the Fed in 2008, market volatility began to subside and betas decreased.

Figure 3: Betas During the Financial Crisis – KBW Bank Index (BKX)

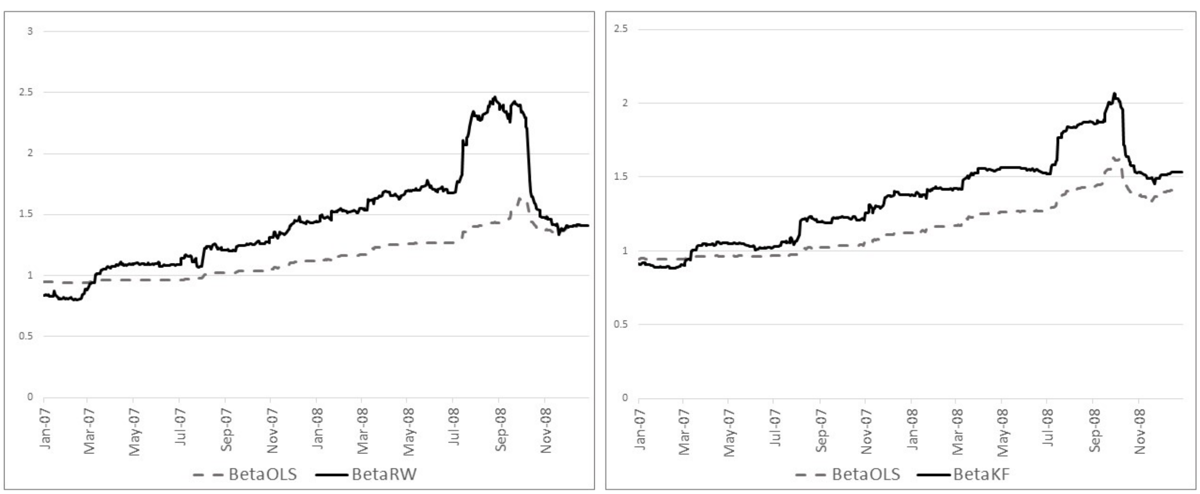


Figure 4: Betas During the Financial Crisis – NASDAQ Bank Index (CBNK)

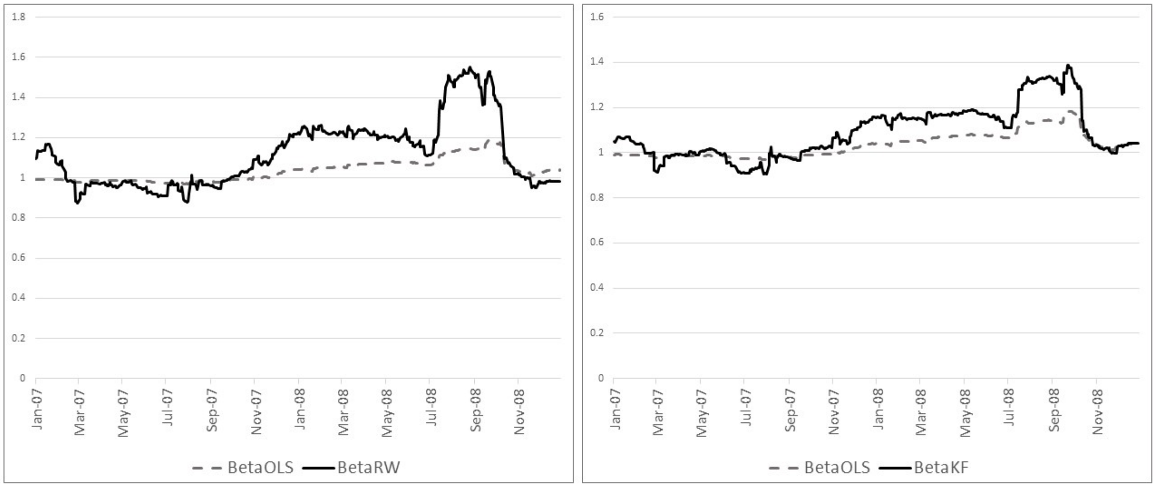


Figure 5: Betas During the Pandemic – KBW Bank Index (BKX)

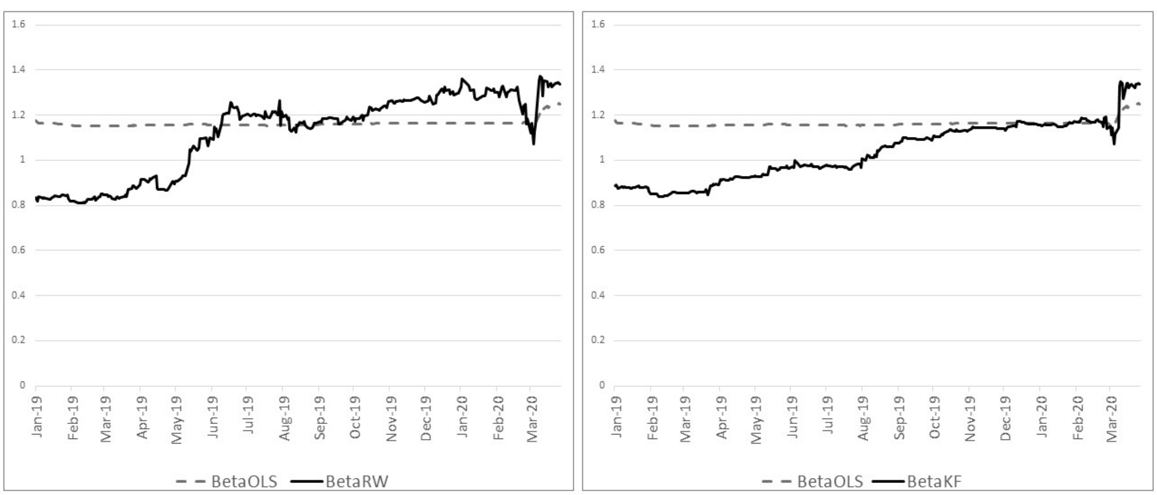
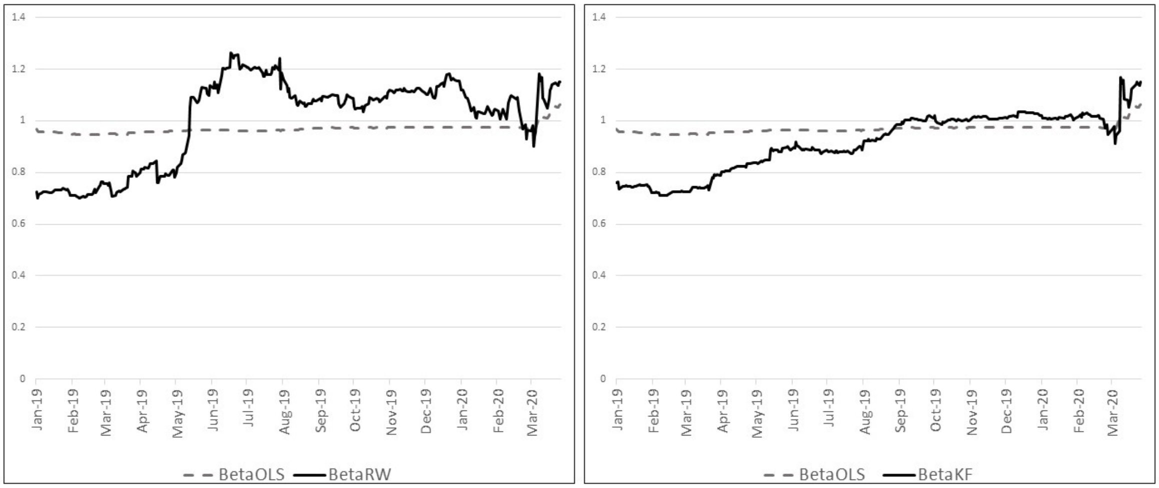


Figure 6: Betas During the Pandemic – NASDAQ Bank Index (CBNK)



Figures 5 and 6 present the dynamics of the beta coefficients prior to and during the Covid-19 pandemic. The estimates based on Kalman filtering were quite stable again, whereas the rolling-window estimates were volatile and exhibited unexpected spikes. Similar to the financial crisis, the KBW betas were greater than the NASDAQ betas during the pandemic.

Prior to the pandemic, the NASDAQ Bank Index had a beta around 1.0, while the KBW Bank Index beta was slightly below 1.2. Hence, stocks in the NASDAQ index moved in tandem with the overall market prior to the pandemic. As the virus became a global health problem, the VIX spiked and the US stock market trended down after February 19, 2020. However, there did not appear to be a significant immediate response in the bank betas to the market volatility brought on by the pandemic until March 9. Unlike the gradual increase in betas during the financial crisis period, the instability in bank betas brought on by the overall market volatility associated with the pandemic was not apparent until March 9. They stabilized somewhat later, but settled at higher levels. The difference in the market reaction between the pandemic versus the financial crisis may be the fact that the pandemic is an unprecedented historical event in recent history, with unpredictable economic and financial implications. This is the first time since the Great Depression that a massive negative demand shock has coincided with a massive negative supply shock, resulting in a serious economic contraction.

The obvious question is: What is so significant about the week of March 9 rather than the starting days of the bear market in February? There are several factors that could explain why volatility surged then. First, on March 9, several states, including Oregon, Washington, California, Maryland, and New York declared a state of emergency. Second, an international travel ban from the Schengen Area was imposed by the United States. And third, an oil price war between major oil producing countries began around this time. Additional factors, such as the economic shutdown in Europe due to the fast spread of the virus in some European countries increased the concerns about the US economy, while the virus began to invade more cities and states in the US. All these events help explain the financial panic that ensued in the US financial markets beginning March 9. Up until that date, the concerns were mainly about China. On that day, the Dow Jones Industrial Average lost more than 2,000 points, the largest intraday point decline ever. Between February 19 and March 9, the VIX more than tripled, and the S&P 500 decreased by about 639 points. The result was one of the biggest shocks to financial assets and the banking industry in US economic history, and the market risk indicators followed suit.

In sum, we found that the betas for both bank indices increased significantly when volatility surged during the financial crisis and the pandemic, particularly when the crises impacted the US domestic economy. The increase in betas during the financial crisis was gradual, while the increase during the pandemic was sudden and sharp. In addition, the beta estimates for the KBW Bank Index were higher than those for the NASDAQ Bank Index during both stock market crashes. Finally, the rise in betas was relatively lower during the pandemic compared to that of the financial crisis, which is likely due to the fact that the banking industry was largely the epicenter of the last crisis.

5. Conclusions

When estimating a firm’s cost of capital, analysts often utilize the CAPM to estimate the cost of the equity component. The CAPM assumes that the relative volatility of the firm’s return compared to the market as a whole (measured by the beta coefficient or systematic risk) remains constant over time. This assumption, however, is faulty as proven by several studies for the US and international markets (Faff et al., 2000a, 2000b, Andersen et al., 2006).

This study examined the relationship between two important bank indices and the S&P 500 index and found that there is instability in bank betas during periods of excessive market volatility, specifically during the global financial crisis of 2007–2009 and the current Covid-19 pandemic. The study tested the stability of beta coefficients using the standard OLS estimation technique. One shortcoming of OLS is that it fails to respond quickly to changes in market volatility. Thus, we applied more rigorous econometric-based techniques, including the RW-OLS and TVC-KF approaches, to examine the stability of beta coefficients and to detect structural breaks during extreme market volatility. The results showed that the RW-OLS estimation procedure captures the structural changes in time-varying betas, but the estimates were quite volatile. Alternatively, the TVC-KF approach produced estimates that are smoother and capture the dynamic changes in market regimes.

The results of this study are important because they provide evidence that support the conclusion that banks might be underestimating their cost of capital, especially during periods of extreme market volatility and regime switching. The conclusions of this study will help banking institutions find more reliable beta estimates and incorporate these estimates into the cost of capital calculations and fair market valuations of bank stocks. Future research may examine time-variant standard deviations and correlations to decompose the effect on the dynamic beta coefficients over time. Researchers can also examine the dynamics of betas over business cycles. Finally, it would be interesting to investigate whether the Kalman filter can be used to forecast the betas and connect these estimates to the cost of capital metrics.

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