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Do Banks Suffer From Stigmatization In Equity Capital Markets?

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Abstract

This Master's Thesis investigates which effect the Federal Reserve's release of detailed Discount Window transaction data on March 31, 2011 had on the borrowing banks' stock performance. Three sets of event studies indicate that those banks did not experience negative abnormal stock returns, rejecting the hypothesis that, in equity capital markets, there is a negative stigma attached to borrowing under the Discount Window facility. This finding provides empirical support for the Dodd-Frank Act's requirement to reveal detailed Discount Window lending data after eight quarters as a tool to improve the transparency of central banks without limiting their effectiveness to act as lender of last resort. Furthermore, the analysis suggests that the Federal Reserve succeeded in designing additional credit and liquidity programs during the financial crisis between 2007 and 2009 as their usage was not associated with negative abnormal stock returns.

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1 Introduction

"In August 2007, ... banks were reluctant to rely on discount window credit to address their funding needs. The banks' concern was that their recourse to the discount window, if it became known, might lead market participants to infer weakness – the so-called stigma problem."

– Bernanke (2009) –

Historically, preventing bank failures from running out of control by discounting, i.e., providing reserves to banks during a financial crisis when nobody else would, was the most important role of the US Federal Reserve System (Mishkin, 2013). In the financial crisis beginning in 2007, the Federal Reserve (Fed) tried to supply liquidity by encouraging banks to borrow from the Discount Window (DW) facility at each regional Fed. However, as short-term funding was drying up, most banks abstained from accessing the DW arguably due to the perceived stigma[1] attached (see Bernanke's quote). This was alarming given that short-term funding became simultaneously more important and more sensitive to banks' reputations than deposits (Berry, 2012). In particular, in order to fund long-term assets, banks relied on obtaining short-term liabilities in the repurchase agreement (repo) market, in which a significant portion of the underlying collateral was comprised of mortgage-backed securities (Cyree et al., 2013). Given the sudden deterioration of subprime mortgage-backed securities and the collapsing mortgage-backed securities market it comes as no surprise that net repo financing provided to US banks and broker-dealers fell by about $1.3 trillion - more than half of its pre-crisis total - between Q2 2007 and Q1 2009 (Gorton and Metrick, 2015). Yet, while "markets were frozen, banks had pulled back very substantially from interbank lending," and the financial system essentially seized up (Paulson, 2008), the Fed was limited in providing liquidity to the banking system through its DW facility, as banks feared being exposed as illiquid. However, as reasonable and legitimate central bankers' concerns about the stigma problem might be, there is limited empirical evidence of its existence during the recent financial crisis. In this Master's Thesis, I take advantage of the Fed's unforeseen release of DW lending data, analyze its effect on the borrowing banks' stock performance, and thereby test whether banks should be afraid of adverse effects in the equity capital markets if their recourse to the DW becomes known.

1.1 The Discount Window

Since the establishment of the Federal Reserve System in 1913 the DW is regarded as a reliable backup source of funding by alleviating liquidity strains for individual deposit-taking institutions. As the lender of last resort, the Fed is tasked with providing liquidity to illiquid but solvent banks. Although those banks are supposed to fund themselves on the interbank market (Selgin, 1993), they face problems if this market stops to function (Armantier

[1] Armantier et al. (2015) define DW stigma as "reluctance to access the DW out of concerns that, if detected, depositors, creditors or analysts could interpret DW borrowing as a sign of financial weakness."

et al., 2015). These are the times when central banks are possibly better suited to supply funding (Freixas et al., 1999; Berger et al., 2000). Following a fundamental change in the Fed's DW policy on January 9, 2003, banks have access to three types of credit on a typically overnight basis subject to pledging satisfying collateral: Primary credit is available to depository institutions in sound financial condition at a rate higher than the Federal Open Market Committee's target rate for federal funds, allowing the Fed to set an upper bound to the interbank lending rate (Mishkin, 2013); secondary credit is available to depository institutions which are not eligible for primary credit when its use is consistent with a bank's timely return to market sources of funding or the orderly resolution of a troubled borrower; lastly, seasonal credit assists small depository institutions in managing recurring intra-yearly swings in funding needs, enabling them to carry fewer liquid assets throughout the cycle.[2]

Whereas DW borrowing takes a back seat in normal times, "usage of these liquidity facilities during the crisis was extraordinary. While DW usage averaged $170 million per day from 2003 to 2006," it climbed to around $31 billion on average from August 2007 to December 2009 (Berger et al., 2017). Nonetheless, as in previous downturns the DW stigma was seen as obstacle to even greater DW borrowing (Madigan and Nelson, 2009; Berry, 2012). Fatally, there are three reasons why the DW stigma may be most detrimental during financial crises. First, central banks are ineffective in supplying much needed liquidity. Second, commercial banks face inadequate alternatives such as fire sales, crippling banks further and reducing financial stability even more. Third, banks avoid increasing risk by extending new loans to the real economy. (Madigan and Nelson, 2009; Duke, 2010)

Yet, it is not self-evident why healthy banks are stigmatized by tapping the DW. For example, in the real estate crisis between the mid 1970s and the early 1980s, several banks visited the discount window frequently and successfully (Cyree et al., 2013). A possible reason may be that banks which obtain DW loans tend to fail subsequently (Schwartz, 2009). As a consequence, Boyson et al. (2017) argue that sound banks may avoid accessing the DW, explaining Peristiani's (1998) observation that DW funding went out of fashion. Besides, Flannery (1996) and Boyson et al. (2017) contend that in normal times, in an economy with developed credit markets, banks have no incentive to borrow from the DW as these loans carry higher interest rates than their short-term secured counterparts in the repo market.

Furthermore, as shown by Philippon (2012) and Ennis (2013) the stigma can only develop if market participants, given asymmetric information, base conclusions concerning banks' financial situation on observed DW usage. Since the Fed, in line with its longstanding policy,[3] does only publish weekly aggregate DW borrowing amounts from each of the twelve district Federal Reserve banks, it is not apparent how depositors, creditors, or analysts could observe banks' recourse to the DW. Nevertheless, banks have reason to believe that the condition is satisfied, i.e., that their DW usage can be unveiled, in one of the three ways:

[2]This and more information on the DW can be found on the Fed websites regarding the regulatory reform and the DW facility.

[3]As opposed to news about monetary policy, which is potentially *informally communicated* to the media and financial sector (Cieslak et al., 2018; Kuttner, 2001; Finer, 2018), the literature provides no indication that information related to DW borrowers is leaked by the Fed (Blinder et al., 2008).

1. Market participants observe market activity and "might have been able to make an educated guess about which firms were borrowing at the Fed's discount window" (Di Leo and Randall, 2011).

2. The media leaks information. For instance, it was revealed that Northern Rock, Deutsche, and Barclays had sought central bank funding.[4]

3. Public Fed reports of aggregate DW borrowing are deciphered. As Peter Fischer, former senior official at the New York Fed's Open Market Desk, recalls "it was reasonably easy to discern who the borrower was if it was a big bank outside New York. As soon as the borrowing was reported, big corporate depositors would call up and ask if a bank was the borrower, and if they were, they would pull their deposit. There was a true stigma attached" (Berry, 2012).

This thesis adds to the body of empirical studies of DW stigma. For instance, Anbil (2017) finds evidence that depositors withdrew more deposits from stigmatized banks during the Great Depression, while Furfine (2001, 2003) has documented an existing stigma in the US interbank market. With regard to the recent financial crisis, Armantier et al. (2015) find that the DW stigma increased the borrowing cost of some banks significantly. In contrast, the key question guiding my research is whether banks suffer from stigmatization in equity capital markets.

1.2 Bloomberg News vs. Federal Reserve Board

In accordance with its more than century-old policy of not revealing details regarding which financial institution borrowed when and how much money against what collateral from the DW, the Fed resisted Bloomberg News' Freedom of Information Act (FOIA) request to disclose this information. As a consequence, Bloomberg filed a lawsuit against the Board of Governors of the Federal Reserve System on November 7, 2008, demanding a release of the data. Besides having attention-grabbing stories about the secretive central bank, bowing to commercial banks and withholding information from the public,[5] the news agency "essentially argued that the risk that the Fed and thus taxpayers would lose money on some of the loans was more important than the risk that disclosure could disrupt the Fed's herculean effort to prevent a collapse of the financial system" (Berry, 2012). On the opposite side, the Fed, mindful of the stigma attached to identified borrowers, refused the demand, citing fears of losing confidence in and between banks (Sellinger, 2009).

[4]See "Northern Rock gets bank bail out", *BBC News* (September 13, 2007), "Fed fails to calm money markets", *The Financial Times* (August 21, 2007), and "Barclays admits borrowing hundreds of millions at Bank's emergency rate", *The Guardian* (August 31, 2007).

[5]For instance, see "Testimony in Support of HR 1207, The Federal Reserve Transparency Act of 2009", *Archives of Financial Services Committee* (September 25, 2009) in which Thomas E. Woods refers to Bloomberg's headline "Fed Defies Transparency Aim in Refusal to Disclose" from November 10, 2008.

Following the release of detailed transaction data for all its other emergency liquidity facilities on December 1, 2010 as required by the Dodd-Frank Act, it was not until March 21, 2011 that the U.S. Supreme Court ultimately ruled that the Fed had to hand over the discount window information to Bloomberg News. Thereupon on March 31, 2011, "Bloomberg News reporters received two CD-ROMs, each containing an identical set of 894 PDF files, from Fed attorney Yvonne Mizusawa at about 9.45 a.m. in the lobby of the Martin Building in Washington" (Torres, 2011). These files contained the "daily borrowing totals for 407 banks and companies that tapped the Federal Reserve emergency programs during the 2007 to 2009 financial crisis" (Ivry and Kuntz, 2011), which is the first time such data have been publicly available in this form.

1.3 Hypotheses

Leveraging this unprecedented event, I test my first hypothesis that the Fed's release of detailed DW transaction data on March 31, 2011 results in abnormal returns of identified DW borrowers' stocks as it contains new information for equity investors.

Following the stigma logic, I expect those abnormal returns to be negative as investors draw negative conclusions about the asset quality of borrowing banks. However, there are also various reasons to expect a positive impact. First, Lee (2009) claims that there is no longer a stigma attached to borrowing from the Fed and further points out that banks could have borrowed from the Fed and earned an essentially risk-free spread by lending to the Treasury. Although these earnings are reflected in borrowing banks' financial statements, investors could derive which banks have abstained from the DW and therefore did not exploit this arbitrage opportunity. Inferring weak management skills based on foregone earnings might then increase borrowing in relation to non-borrowing banks' share price, culminating in positive abnormal returns. Moreover, a positive stock market reaction might be grounded in reduced uncertainty surrounding banks' asset quality (Duffie and Lando, 2001). Finally, and closely related to the previous argument, markets could react positively on news that certain banks were able to borrow under the primary or secondary credit program as this implies that they were able to provide high quality collateral and were illiquid but not insolvent.

With regard to the three ways of unveiling DW usage, it is also possible that there is no market reaction at all. If investors were already aware or at least relatively certain which banks borrowed under the DW, the release of detailed DW transaction data would not contain new, market-sensitive information. Consequently, there would be no abnormal return. Furthermore, along the reasoning of Gorton and Ordoñez (2014), the impact of releasing asymmetric information differs between crisis and non-crisis times. Since the Fed's disclosure occurred after the most severe phase of the crisis, the abnormal returns might be insignificant or non-existent at all.

Based on my first hypothesis and utilizing the Fed's release of detailed transaction data for all its facilities except the DW on December 1, 2010, I then test my second hypothesis that abnormal returns differ by i) facility, ii) bank type, iii) financial situation, and iv) location.

To overcome the perceived stigma and address specific problems in different parts of the financial system during the financial crisis, the Fed created a set of additional facilities[6] (Armantier et al., 2015):

- Under the Term Auction Facility (TAF), created on December 12, 2007, the Fed extended short-term loans of fixed amounts to depository institutions at interest rates determined in a competitive bidding process. Crucially, by introducing the auction feature and crediting the loans only after three days, the Fed aimed to overcome the stigma concerns (Armantier et al., 2015).
- Under the Term Securities Lending Facility (TSLF), created on March 11, 2008, the Fed lent Treasury securities to primary dealers against a broad range of less liquid collateral as the Treasury collateral obtained via the TSLF was easier to finance in the repo market (Acharya et al., 2017).
- Under the Primary Dealer Credit Facility (PDCF), created on March 16, 2008, primary dealers could borrow on similar terms as banks using the traditional DW.
- Under the Asset-Backed Commercial Paper Money Market Mutual Fund Liquidity Facility (AMLF), created on September 19, 2008, the Fed provided loans to banks and primary dealers so that they could purchase asset-backed commercial paper from money market mutual funds.
- Under the Commercial Paper Funding Facility (CPFF), created on October 7, 2008, the Fed founded a special purpose vehicle to purchase highly-rated, three-month unsecured and asset-backed commercial paper directly from eligible issuers.

In addition, on March 7, 2008 the Fed started to expand its open market operations (STOMO) to alleviate liquidity strains in a number of credit markets. For example, by conducting Single-Tranche Term Repurchase Agreements with primary dealers as counterparties it supported the functioning of funding markets, decreased long-term interest rates, and helped to improve broader financial markets conditions.

Based on the special design of the TAF and consistent with the findings of Armantier et al. (2015), I expect differences in abnormal returns between banks tapping the TAF and DW. For example, TAF banks might experience positive abnormal returns as they benefit from lending additional funds with a spread and communicating asset quality by posting high-quality collateral without conveying the impression that they depend on funding by the Fed. In contrast, for banks tapping the PDCF instead of the DW, I expect the same stigma considerations to apply, since investors hold shares in the parent company and not individual legal entities such as the banks' US securities franchises.

[6]See the Fed's website on its crisis response for further details.

As shown in Cyree et al. (2013), I also anticipate that market participants struggle to identify what funding through the numerous facilities implies for the solvency of banks with different business models and therefore expect different abnormal returns for investment, too-big-to-fail, and traditional banks. Additionally, I address the fact that some investors might no longer penalize illiquidity during the crisis if a bank is in a sound financial situation at the time of the event,[7] and lastly check if the abnormal returns differ by banks' Fed district as DW usage of non-NY banks might have been easier to discern.

Testing these hypotheses and providing empirical evidence whether banks suffer from stigmatization in equity capital markets is important for a number of reasons. In a narrow setting it enriches the debate of whether the Fed was right to resist and delay disclosing DW lending data to the public. More importantly, it is relevant from a regulatory point of view. Acknowledging possible side effects of timely disclosure of DW lending data by borrower, the Dodd-Frank Act introduces an eight quarter lag after which the Fed is obliged to reveal this information. If banks' market capitalization declined upon the unexpected disclosure on March 31, 2011, then banks have one more reason to avoid DW funding. Deciding whether the increase in transparency is worth the adverse consequences in a future crisis is then up for debate. Additionally, determining whether the stigma differs by facility can guide the effective design of central bank credit and liquidity programs and is relevant for steering monetary policy as the discount rate is supposed to be the upper bound for the Federal Funds rate. If borrowing from the DW is no option or in fact more expensive than the difference between the interbank borrowing and discount rate,[8] then central banks need to reconsider the DW as a tool to control the variance in the interbank interest rate.

2 Data

The analysis builds upon a dataset, obtained under a FOIA request, released by Bloomberg News of individual banks' borrowing activity under the Fed's (crisis) facilities. Specifically, the data details how much each bank, including all subsidiaries, owed the Fed under each of the seven credit and liquidity programs described in Subsection 1.3 on a daily basis between August 1, 2007 and April 30, 2010; thereby covering the whole time period when those facilities were accessible. Moreover, the companies' Bloomberg tickers[9] are provided as are the parent companies' home countries and Bloomberg Industry Classification codes.

Modifying this dataset, I began with aligning foreign firms' Bloomberg tickers to ensure identical trading days and underlying stock market characteristics. For example, the ticker of Deutsche Bank AG [DBK_GR_Equity] was changed to [DB_US_Equity]. Subsequently, the dataset was supplemented by time series data for each firm's total return index gross dividends. Besides identifiers for each bank's federal reserve district, I further added the fol-

[7] The term *event* will be defined in Subsection 3.1.

[8] If banks' market capitalization decreases, then their cost of equity and thus of average capital increases.

[9] Bloomberg tickers are strings of characters or numbers to identify a company uniquely in Bloomberg.

lowing selected balance sheet and income statement data as reported to the Federal Deposit Insurance Corporation (FDIC), thereby ensuring consistency in each item's definition and ultimately guaranteeing comparability: Tier 1 & 2 capital to risk-weighted assets, common equity to assets, return on average equity, net interest income, and net income.

Lastly, the five common asset-pricing research factors[10] defined in the notes on Table 1 and a US bank return index (capturing depository institutions, banks under Federal Reserve supervision, and commercial banks) from Kenneth R. French's website were included.

Using this raw data, the sample is constructed as follows: Since the event studies analyze stock returns, a total of 206 private or delisted firms is excluded as are 73 firms, which were not actively traded in the period analyzed, decreasing the sample size to 128 firms. However, leasing arms of corporations such as Ford or GE and insurance companies such as AIG or Prudential still belong to this set of companies. Excluding the 42 firms not classified as banks then leads to a total of 86 banks, constituting the sample.

After all, these 86 banks differ in various characteristics, motivating the creation of several subsets for which the aggregated stock performance is shown in Figure 1, which gives an impression of the financial crisis in terms of banks' stock performance. In order to test the first hypothesis, the 69 banks which accessed the DW are allocated to subset 1, whereas the remaining 17 banks are contained in subset 2. Subsequently, subset 1 is further broken down to test the second hypothesis. Following Cyree et al. (2013), the 69 banks are grouped into 4 investment banks[11] (IB), 8 too-big-to-fail banks[12] (TBTF), and 57 traditional banks (Trad) which belong to neither of the aforementioned two groups, constituting subsets 3 to 5. At any given day the 69 banks are also grouped into quartiles based on their Tier 1 & 2 capital to risk-weighted assets ratio,[13] before the quarter with the highest capital adequacy (sound) is assigned to subset 6 while the quarter with the lowest capital adequacy (unsound) is assigned to subset 7. Furthermore, subsets 8 to 13, which are not mutually exclusive, are constructed based on participation in the remaining six Fed facilities (AMLF, CPFF, PDCF, STOMO, TAF, TSLF). For example, subset 8 contains the 5 banks that used both DW and AMLF while subsets 9 to 13 contain 17, 9, 9, 67, and 9 banks, respectively.[14] Finally, subset 14 contains the 25 DW banks of the second federal reserve district (NY), i.e., the banks which borrowed under the DW and are supervised by the Federal Reserve Bank of New York, while subset 15 contains the remaining 44 banks (Non-NY).

[10] Fama and French (1992, 2015) show that market β, size (market capitalization), book-to-market equity, profitability and investment capture the cross-sectional variation in average stock returns. A detailed description of the five factors can be found here.

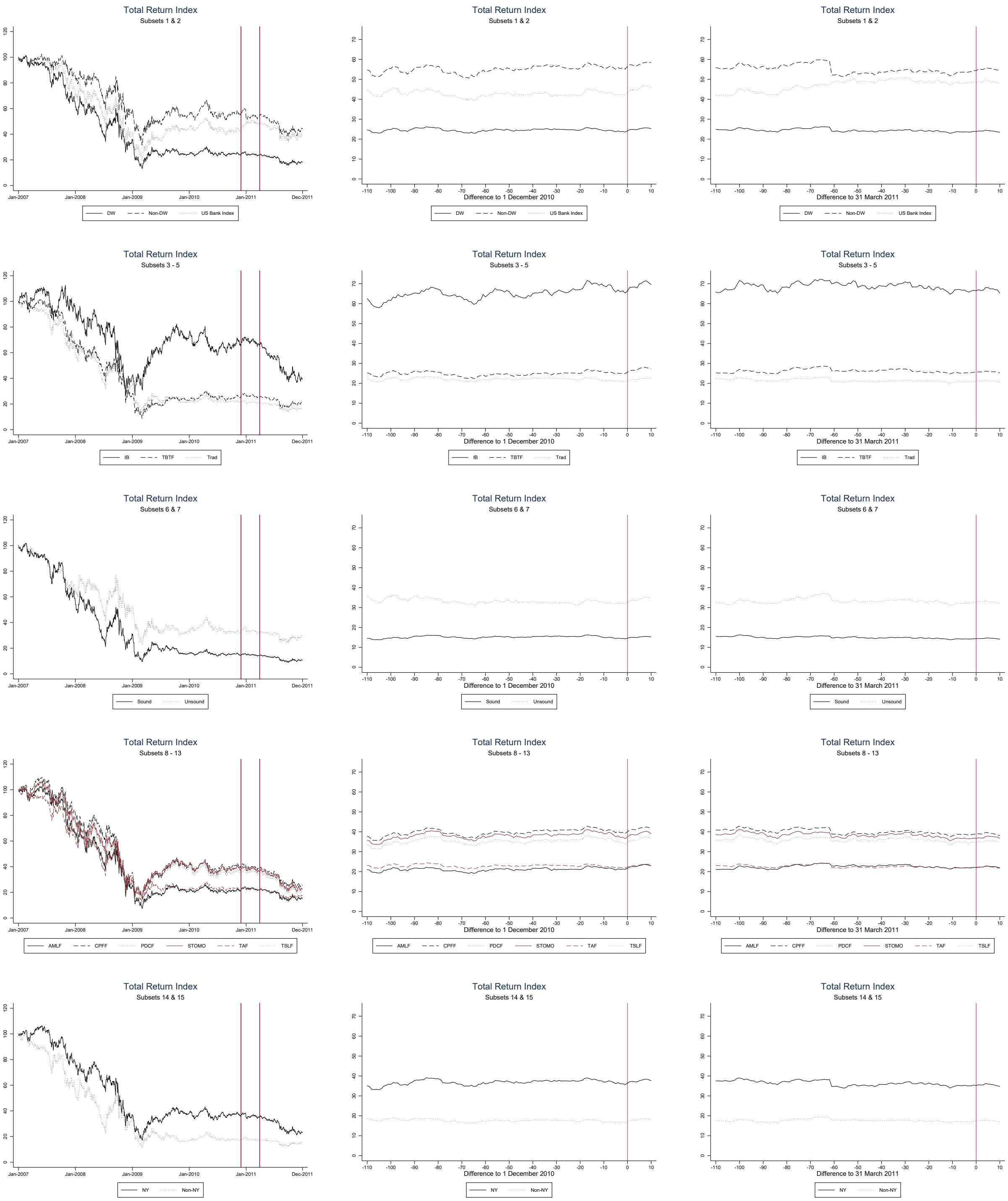
[11] Based on the self-description of their business model Bank of America, Goldman Sachs, J.P. Morgan-Chase, and Morgan Stanley belong to this group.

[12] Based on the Fed's announcement in April 2009 that these banks need to be stress-tested Citigroup, Fifth Third Bancorp, KeyCorp, PNC Financial Services, Regions Financial Corp., State Street Corp., SunTrust Banks, and U.S. Bancorp belong to this group.

[13] The remaining FDIC balance sheet and income statement items are used to verify robustness.

[14] Resulting from the eligibility criteria but also by coincidence, the set of banks which used the DW and TSLF and engaged in the Single-Tranche Open Market Operations is identical. Consequently, subsets 11 and 13 do not differ.

Figure 1: Bank Stock Performance by Subset



Total Return Indices were rebased to 100 on January 3, 2007. The first vertical line on December 1, 2010 indicates the day when the Fed released the transaction data for all its credit and liquidity programs excluding the DW. The second vertical line on March 31, 2011 indicates the day when the Fed released the transaction data for its DW facility. The difference to December 1, 2010 and March 31, 2011 is measured in trading days. Source: Author's rendering of Bloomberg data (2018).

3 Methodology

The two hypotheses underlying the research question are tested by conducting event studies for the various subsets. From one of the first event studies published by Dolley (1933) to the ones of Ball and Brown (1968) and Fama et al. (1969) the event study methodology has improved remarkably. Even today minor modifications still emerge due to problems arising from statistical assumptions made in earlier papers which do not hold in practice (Campbell et al., 1997). Nevertheless, the idea that security prices will immediately reflect the impact of an event if the market incorporates new information efficiently remains unchanged.

3.1 Outline of Event Study

In this analysis, the release of information regarding the banks which borrowed and the time when they borrowed under the Fed's facilities during the financial crisis is classified as event. Although it is clear that the Fed disclosed the DW transaction data on March 31, 2011,[15] it is unclear when the information precisely entered the market for two reasons. On the one hand, the Fed released the transaction data regarding all its facilities excluding the DW on December 1, 2010, possibly enabling the market to infer the potentially new information on banks contained in observing the DW usage. On the other, DW usage can be unveiled in the ways described in Subsection 1.1. Mitigating these concerns, three sets of event studies, each with different event date, are conducted. The first and second set of event studies are based on December 1, 2010 and March 31, 2011, respectively, and jointly examining the results helps addressing the first flaw. The second flaw is then accounted for by the third set of event studies which is based on the date when a bank accessed the DW or, for the banks in subset 2, any other of the Fed's credit and liquidity programs for the first time.

Based on the event date an event window of length L is set, including both five trading days before and after the event. Within this window security returns on a given trading day are indexed by τ. The reason for analyzing returns over multiple days is twofold: First, the market might obtain information or anticipate the event prior to the event date. Second, the market needs time to incorporate and reflect the new information in a security's price (Kothari and Warner, 2007). Naturally, the results might be sensitive to the event window's length, which is fairly arbitrary. Although the event's impact is expected to occur exactly at the event day and is zero on the pre- and succeeding days, the test might fail to reject the null hypothesis of no abnormal return. On the one hand, the test statistic might fail to detect a small but persistent impact over several days if the event window is too short. On the other, the test statistic might fail to detect a significant impact on the event day if

[15] While the Q1 Earnings season for large-cap US Financials does not kick off before the second April week, a Factiva-News analysis reveals that the Fed's disclosure is apparently an *abnormal* event that day: On Thursday, March 31, 2011, (Wednesday, March 31, 2010) there were 8,000+ (8,000+) US news stories, 345 (65) US Banking news stories, and 164 (0) US Banking news stories containing the term "Discount Window".

there is no movement in security prices around this day and the event window is too long. The resulting trade-off is resolved by choosing multiple event windows of different length and reporting not only the cumulative test statistics over the whole period but also for each event day.

In addition, an estimation window of length T is set, including the 100 trading days preceding the first day in the event window. Within the estimation window, security returns on a given trading day are indexed by t. Again, the chosen length is arguably arbitrary and involves trading-off the increasing precision of parameter estimates and the increasing probability of structural breaks in the return time series (Armitage, 1995). Since Peterson (1989) finds that estimation periods typically range from 100 to 300 trading days for daily studies, the analysis was also conducted with an estimation window of 300 trading days without significantly changing the results.[16]

3.2 Normal and Abnormal Returns

Excess stock returns in the estimation, r_{it}^e, and event window, $r_{i\tau}^e$, are calculated as

$$r_{it}^e = ln\left(\frac{TRI_{it}}{TRI_{i,t-1}}\right) - r_{Ft} \tag{1}$$

and

$$r_{i\tau}^e = ln\left(\frac{TRI_{i\tau}}{TRI_{i,\tau-1}}\right) - r_{F\tau}, \tag{2}$$

where TRI is the total return index gross dividends and r_F is the Treasury bill rate. Following Brown and Warner (1980), residuals and abnormal returns are estimated using Mean, Market, and One-Factor models. Moreover, the Five-Factor model (Fama and French, 1992, 1993, 2015) is implemented. Since Fama and French (1992) explicitly exclude financial firms in the creation of their research factors, the Five-Factor model is further augmented with an industry portfolio, extracting the most of the cross-correlations from the residuals in comparison. Lastly, a pure Industry model is estimated. The models are defined in Table 1.

[16] An extract of these results is provided in Appendix D.

Table 1: Asset Pricing Models

Label	Specification
Residual Generating Models in Estimation Period: $t = 1, ..., T$	
Mean	$u_{it} = r^e_{it} - \sum_{t=1}^{T} \frac{r^e_{it}}{T}$
Market	$u_{it} = r^e_{it} - r^e_{Mt}$
One-Factor	$u_{it} = r^e_{it} - a_i - b_i r^e_{Mt}$
Five-Factor	$u_{it} = r^e_{it} - a_i - b_i r^e_{Mt} - s_i SMB_t - h_i HML_t - r_i RMW_t - c_i CMA_t$
Six-Factor	$u_{it} = r^e_{it} - a_i - b_i r^e_{Mt} - s_i SMB_t - h_i HML_t - r_i RMW_t - c_i CMA_t - i_i I^e_t$
Industry	$u_{it} = r^e_{it} - I^e_t$
Abnormal Return Generating Models in Event Period: $\tau = 1, ..., L$	
Mean	$AR_{i\tau} = r^e_{i\tau} - \sum_{t=1}^{T} \frac{r^e_{it}}{T}$
Market	$AR_{i\tau} = r^e_{i\tau} - r^e_{M\tau}$
One-Factor	$AR_{i\tau} = r^e_{i\tau} - a_i - b_i r^e_{M\tau}$
Five-Factor	$AR_{i\tau} = r^e_{i\tau} - a_i - b_i r^e_{M\tau} - s_i SMB_\tau - h_i HML_\tau - r_i RMW_\tau - c_i CMA_\tau$
Six-Factor	$AR_{i\tau} = r^e_{i\tau} - a_i - b_i r^e_{M\tau} - s_i SMB_\tau - h_i HML_\tau - r_i RMW_\tau - c_i CMA_\tau - i_i I^e_\tau$
Industry	$AR_{i\tau} = r^e_{i\tau} - I^e_\tau$

Notation is defined as follows: r^e_{it} and r^e_{Mt} are security and market excess returns over the Treasury bill rate, respectively; SMB_t is the small-minus-big market capitalization portfolio return, HML_t is the high-minus-low book-to-market equity portfolio return, RMW_t is the robust-minus-weak profitability portfolio return, and CMA_t is the conservative-minus-aggressive investment portfolio return; I^e_t is the industry excess return; a_i, b_i, s_i, h_i, r_i, c_i, and i_i are estimated OLS coefficients; i, t, and τ indicate the security, estimation day, and event day, respectively.

3.3 Test Statistics

Under the null hypothesis the returns' mean or variance is not affected by the event. Hence, the distribution of abnormal returns allows to test this hypothesis and test statistics are typically calculated for each security and each day in the event window indexed by $i\tau$, cumulated over securities on each day in the event window indexed by τ, or cumulated over both securities and days in the event window. For example, in the *Traditional Method* of Brown and Warner (1980) security i's abnormal return on a day in the event window is standardized by the individual security's standard deviation estimated over the estimation window:

$$t^{BW}_{i\tau} = \frac{AR_{i\tau}}{\left(\frac{1}{T-1}\sum_{t=1}^{T}\left(u_{it} - \sum_{t=1}^{T}\frac{u_{it}}{T}\right)^2\right)^{1/2}} = \frac{AR_{i\tau}}{\left(s^2(u_{it})\right)^{1/2}} = \frac{AR_{i\tau}}{s(u_{it})}. \tag{3}$$

Similarly, the t-statistic aggregated over securities is given by

$$t_{\tau}^{BW} = \frac{\frac{1}{N}\sum_{i=1}^{N} AR_{i\tau}}{\frac{1}{N}\left(\sum_{i=1}^{N} s^2(u_{it})\right)^{1/2}} = \frac{\sum_{i=1}^{N} AR_{i\tau}}{\left(\sum_{i=1}^{N} s^2(u_{it})\right)^{1/2}}. \tag{4}$$

With his *Standardized Residual Method* Patell (1976) follows a related approach when he estimates scaled abnormal returns $SAR_{i\tau}$ by standardizing each firm's abnormal return with its individual standard deviation estimated over the estimation window:

$$t_{i\tau}^{P} = \frac{AR_{i\tau}}{\left((1+c_{i\tau})\frac{1}{T-1}\sum_{t=1}^{T} u_{it}^2\right)^{1/2}} = SAR_{i\tau}, \tag{5}$$

where the term $c_{i\tau}$ of the form $\mathbf{x}_{\tau}^{'}(\mathbf{X}^{'}\mathbf{X})^{-1}\mathbf{x}_{\tau}$ corrects for the estimation of the regression parameters in the estimation period, with vector $\mathbf{x}_{\tau}$ of regressor values (including the constant) on event day τ, and matrix $\mathbf{X}$ of regressor values in the estimation period. In contrast to Brown and Warner (1980), it is these scaled abnormal returns which are aggregated over securities, thereby weighting extreme abnormal returns less due to their higher standard deviation and emphasizing more reliable abnormal returns due to their lower standard deviation:

$$t_{\tau}^{P} = \frac{\frac{1}{N}\sum_{i=1}^{N} SAR_{i\tau}}{\frac{1}{N}\left(\sum_{i=1}^{N} 1\right)^{1/2}} = \frac{\sum_{i=1}^{N} SAR_{i\tau}}{\sqrt{N}}. \tag{6}$$

However, the t-statistics in both approaches are prone to volatility changes and cross-sectional correlation and tend to overreject the null hypothesis if the constant variance and cross-sectional independence assumptions do not hold (Kothari and Warner, 2007). In event studies these two assumptions are disputable. On the one hand, either the event itself or the factors that led to it are potentially increasing uncertainty and thus volatility of returns (Brooks, 2008). On the other, and especially when the sample firms have common event days, there is no reason to assume that abnormal returns are cross-sectionally independent (Kothari and Warner, 2007). In presence of both volatility increases within the event window and cross-sectional dependence of abnormal returns the variance estimate would be too low and the null hypothesis of no abnormal returns would be rejected too often.

The first problem of event-induced volatility changes is addressed by Charest (1978) in his *Ordinary Cross-Sectional Method*. He estimates the variance during the event window using each firm's abnormal return on a single day in the event window

$$t_{i\tau}^{C} = \frac{AR_{i\tau}}{\left(\frac{1}{N-1}\sum_{i=1}^{N}\left(AR_{i\tau} - \sum_{i=1}^{N}\frac{AR_{i\tau}}{N}\right)^2\right)^{1/2}} = \frac{AR_{i\tau}}{\left(s^2(AR_{i\tau})\right)^{1/2}} = \frac{AR_{i\tau}}{s(AR_{i\tau})} \tag{7}$$

but, like Brown and Warner (1980), does not scale extreme abnormal returns when aggregating:

$$t_{\tau}^{C} = \frac{\frac{1}{N}\sum_{i=1}^{N} AR_{i\tau}}{\frac{1}{N}\left(\sum_{i=1}^{N} s^2(AR_{i\tau})\right)^{1/2}} = \frac{\frac{1}{N}\sum_{i=1}^{N} AR_{i\tau}}{\left(\frac{1}{N^2} N s^2(AR_{i\tau})\right)^{1/2}} = \frac{\sum_{i=1}^{N} AR_{i\tau}}{\left(N s^2(AR_{i\tau})\right)^{1/2}}. \tag{8}$$

Therefore, Boehmer et al. (1991) combine Patell's and Charest's t-statistics in their *Standardized Cross-Sectional Method* by first obtaining scaled abnormal returns and thereupon following Charest's approach:

$$t_{i\tau}^{BMP} = \frac{SAR_{i\tau}}{\left(\frac{1}{N-1}\sum_{i=1}^{N}\left(SAR_{i\tau} - \sum_{i=1}^{N}\frac{SAR_{i\tau}}{N}\right)^2\right)^{1/2}} = \frac{SAR_{i\tau}}{\left(s^2(SAR_{i\tau})\right)^{1/2}} = \frac{SAR_{i\tau}}{s(SAR_{i\tau})} \tag{9}$$

and

$$t_{\tau}^{BMP} = \frac{\frac{1}{N}\sum_{i=1}^{N} SAR_{i\tau}}{\frac{1}{N}\left(\sum_{i=1}^{N} s^2(SAR_{i\tau})\right)^{1/2}} = \frac{\frac{1}{N}\sum_{i=1}^{N} SAR_{i\tau}}{\left(\frac{1}{N^2} N s^2(SAR_{i\tau})\right)^{1/2}} = \frac{\frac{1}{N}\sum_{i=1}^{N} SAR_{i\tau}}{\left(\frac{1}{N} s^2(SAR_{i\tau})\right)^{1/2}}. \tag{10}$$

Since these t-statistics still rely on the assumption of cross-sectionally independent abnormal returns, Kolari and Pynnönen (2010) adjust them in their *Standardized Adjusted Cross-Sectional Method* by deriving an unbiased estimator of the variance if scaled abnormal returns are not cross-sectionally independent (a derivation in style of Kolari and Pynnönen (2010) can be found in Appendix A):

$$t_{i\tau}^{KP} = \frac{SAR_{i\tau}}{\left(\frac{s^2(SAR_{i\tau})}{1-\bar{r}}\right)^{1/2}} = \frac{SAR_{i\tau}\sqrt{1-\bar{r}}}{\left(s^2(SAR_{i\tau})\right)^{1/2}} = \frac{SAR_{i\tau}\sqrt{1-\bar{r}}}{s(SAR_{i\tau})} = t_{i\tau}^{BMP}\sqrt{1-\bar{r}}, \tag{11}$$

where $\overline{r}$ is the average of the sample cross-correlations of the estimation period residuals. Kolari and Pynnönen (2010) then conduct extensive simulations in order to test the performance of their t-statistic aggregated over securities

$$t_{\tau}^{KP} = \frac{\frac{1}{N}\sum_{i=1}^{N} SAR_{i\tau}\sqrt{1-\overline{r}}}{\left(\frac{1}{N}s^2(SAR_{i\tau})(1+(N-1)\overline{r})\right)^{1/2}} = t_{\tau}^{BMP}\sqrt{\frac{1-\overline{r}}{1+(N-1)\overline{r}}} \tag{12}$$

and conclude that it is robust to both event-induced volatility changes and cross-sectional correlation, while other t-statistics such as those of Patell (1976) and Boehmer et al. (1991) among others reject the null hypothesis of no mean event effect too often.

As mentioned before, the analysis centers not only around abnormal returns cumulated over securities on each day in the event window but also cumulated over both securities and days in the event window. Therefore, the corresponding cumulative t-statistics are given by

$$t^{x} = \frac{\sum_{\tau=1}^{L} t_{\tau}^{x}}{\sqrt{L}}, \tag{13}$$

where $x \in \{BW, P, C, BMP, KP\}$.

4 Results

Centering around the results for the three sets of event studies, i.e., event studies (1) for which the event date is December 1, 2010 when the Fed released the transaction data for all its credit and liquidity programs excluding the DW in Table 3, event studies (2) for which the event date is March 31, 2011 when the Fed released the transaction data for its DW facility in Table 2, and event studies (3) for which the event data varies depending on a given bank's first recourse to the DW or, for the banks in subset 2, to any other of the Fed's facilities in Table 4, this section aims to test the two hypotheses.

Testing the first hypothesis, the test statistic of Kolari and Pynnönen (2010) for subset 1 in Table 2 indicates that on average DW borrowers do not experience an abnormal return upon the release of the DW transaction data independent of the length of the event window. Further, with regard to the second hypothesis, there is no abnormal return for any of the subsets on the event day itself. Perhaps most importantly, it stands out that for any of the subsets and independent of the event window's length the values of t^{KP} are always greater than zero, thereby rejecting my expectation of negative abnormal returns associated with stigmatization in equity capital markets.

Table 2: Values of t^{KP} - Event Studies (2)

Subsets	$\tau \in [-5, 5]$	$\tau \in [-3, 3]$	$\tau = 0$	$\tau \in [0, 3]$	$\tau \in [0, 5]$
1 (DW)	0.833	0.863	0.641	0.608	1.029
2 (Non-DW)	0.992	1.313	0.854	1.115	1.399
3 (IB)	1.325	1.772	1.104	1.607	2.202*
4 (TBTF)	1.641	1.486	0.869	1.302	1.596
5 (Trad)	0.796	0.817	0.587	0.600	0.990
6 (Sound)	1.710	1.283	0.815	1.535	2.200
7 (Unsound)	0.811	0.976	0.926	0.069	0.429
8 (AMLF)	2.530*	2.266*	1.058	1.839	2.901*
9 (CPFF)	0.345	0.679	0.508	0.659	0.928
10 (PDCF)	0.523	0.662	0.439	0.481	1.375
11 (STOMO)	1.208	1.130	0.405	0.866	1.973*
12 (TAF)	0.832	0.853	0.596	0.612	0.997
13 (TSLF)	1.208	1.130	0.405	0.866	1.973*
14 (NY)	0.302	0.553	0.249	0.319	0.745
15 (Non-NY)	1.236	1.120	0.848	0.733	1.123

The event date is March 31, 2011 when the Fed released the transaction data for its DW facility. The subsets are described in Section 2. Columns 2 to 6 show cumulative t^{KP}-statistics for event windows of different length as derived in Subsection 3.3. For instance, $\tau \in [-5, 5]$ implies that L is equal to 11. Residuals and abnormal returns are estimated based on the Six-Factor Model from Table 1. Asterisks indicate significant differences from zero at the 5% level or smaller.

Even though there are multiple possibilities to explain these findings, three cases deserve special attention. First, market participants may have been unable to grasp the released information immediately and therefore failed to draw conclusions about the borrowing banks' fair market valuation. This line of thought gains further empirical support when concentrating on the cumulative test statistic for the event window from $\tau = 0$ to $\tau = 5$ which signals positive abnormal returns for subsets 3, 8, 11, and 13, driven by relatively high values of t_4^{KP} and t_5^{KP} as shown in Appendix B. In addition, the finding that only banks in certain subsets experience abnormal returns is not inconceivable. For example, all of the four subsets contain particularly large, as measured by their total assets, financial institutions,[17] which also act as primary dealers. However, it is questionable whether particularly high abnormal returns on day 4 and 5 in the event window are still the result of the DW transaction data release.

Another reasonable answer may be that the market considers the given type of confidential regulator information simply irrelevant. Lastly, the information may have already been priced in which would explain that the release did not result in abnormal returns. This

[17]Subset 3 contains BAML, JPM, MS, and GS; subset 8 contains BAML, Citi, JPM, State Street, and SunTrust; subsets 11 and 13 are identical and contain BAML, Barclays, BNP, Citi, Deutsche, GS, HSBC, JPM, and MS.

Table 3: Values of t^{KP} - Event Studies (1)

Subsets	$\tau \in [-5, 5]$	$\tau \in [-3, 3]$	$\tau = 0$	$\tau \in [0, 3]$	$\tau \in [0, 5]$
1 (DW)	0.052	0.336	2.407*	1.874	1.644
2 (Non-DW)	−1.234	−0.729	1.055	−0.400	−0.737
3 (IB)	0.907	−2.616*	0.200	−0.011	−0.193
4 (TBTF)	1.105	1.176	−0.512	0.387	0.799
5 (Trad)	−0.103	0.261	2.530*	1.839	1.455
6 (Sound)	−0.645	−0.298	1.917	1.472	1.343
7 (Unsound)	1.027	1.244	1.982*	1.780	1.511
8 (AMLF)	0.177	−0.957	−0.010	−0.232	−0.728
9 (CPFF)	−1.235	−1.008	1.227	0.648	0.822
10 (PDCF)	−2.801*	−2.263*	1.189	0.606	0.694
11 (STOMO)	−2.754*	−2.145*	0.499	0.170	0.278
12 (TAF)	0.102	0.442	2.344*	1.841	1.573
13 (TSLF)	−2.754*	−2.145*	0.499	0.170	0.278
14 (NY)	−1.815	−1.661	1.140	0.329	0.473
15 (Non-NY)	1.487	1.758	2.224*	2.331*	1.824

The event date is December 1, 2010 when the Fed released the transaction data for all its credit and liquidity programs excluding the DW. The subsets are described in Section 2. Columns 2 to 6 show cumulative t^{KP}-statistics for event windows of different length as derived in Subsection 3.3. For instance, $\tau \in [-5, 5]$ implies that L is equal to 11. Residuals and abnormal returns are estimated based on the Six-Factor Model from Table 1. Asterisks indicate significant differences from zero at the 5% level or smaller.

idea is backed by the results in Table 3. In contrast to Table 2, here, the average abnormal return for all DW banks and various subsets is statistically significantly different from zero on the event day, casting doubt on the aforementioned possibilities that the market needs more than three trading days to react or deems the information not market-sensitive.

Even though the results in Table 3 do not capture the effect of releasing DW transaction data, the outcome is in line with the previous finding that the abnormal returns are either not significant on average or actually positive. Consequently and jointly interpreting the results in Tables 2 and 3, it seems unlikely that the market had already priced in the information contained in the DW transaction data before December 1, 2010 as one could have hypothesized based on the idea that market participants observe market activity and "might have been able to make an educated guess about which firms were borrowing at the Fed's discount window" (Di Leo and Randall, 2011).

This reasoning is further supported by the very limited number of media reports singling out individual DW borrowers, significant abnormal returns for banks outside of the second federal reserve district, i.e., subset 15 in Table 3, and the results in Table 4, which do not imply abnormal returns for DW borrowers. Rather, it seems that the release of transaction data for all the other credit and liquidity programs enabled investors to anticipate the information contained in the DW transaction data.

Table 4: Values of t^{KP} - Event Studies (3)

Subsets	$\tau \in [-5, 5]$	$\tau \in [-3, 3]$	$\tau = 0$	$\tau \in [0, 3]$	$\tau \in [0, 5]$
1 (DW)	1.544	1.491	1.035	1.542	1.435
2 (Non-DW)	−1.179	−1.610	−2.326*	−1.431*	−0.501
3 (IB)	0.340	1.046	0.623	1.219	0.679
4 (TBTF)	1.234	0.868	−0.509	0.904	1.220
5 (Trad)	1.621	1.443	1.113	1.394	1.319
6 (Sound)	2.337*	1.121	−0.083	0.986	2.450*
7 (Unsound)	1.092	0.769	0.512	1.035	1.064
8 (AMLF)	1.539	−0.287	−0.277	0.048	0.406
9 (CPFF)	1.277	1.598	0.514	1.476	1.143
10 (PDCF)	0.333	0.756	0.615	0.779	0.587
11 (STOMO)	0.847	1.444	1.124	1.737	1.219
12 (TAF)	1.692	1.371	0.920	1.357	1.344
13 (TSLF)	0.847	1.444	1.124	1.737	1.219
14 (NY)	1.381	1.129	0.439	1.117	1.361
15 (Non-NY)	1.094	1.214	1.098	1.263	0.986

The event date varies depending on a given bank's first recourse to the DW or, for the banks in subset 2, to any other of the Fed's credit and liquidity programs. The subsets are described in Section 2. Columns 2 to 6 show cumulative t^{KP}-statistics for event windows of different length as derived in Subsection 3.3. For instance, $\tau \in [-5, 5]$ implies that L is equal to 11. Residuals and abnormal returns are estimated based on the Six-Factor Model from Table 1. Asterisks indicate significant differences from zero at the 5% level or smaller.

Shifting the focus to the various subsets in Table 3, it becomes clear that the overall significantly positive abnormal return for DW borrowers is driven by the positive abnormal return for traditional banks whereas the abnormal return for investment and too-big-to-fail banks is not statistically different from zero.

In contrast, the financial situation does not seem to be an explanatory factor, since the difference in the test statistics for subsets 6 and 7 is insignificant. Moreover, regarding the facilities used, the empirical evidence is mixed, since only banks which accessed TAF register significantly positive abnormal returns. While it is reasonable that the Fed has been successful in eliminating the stigma by the special design of this facility as hinted at in Armantier et al. (2015), the evidence based on the results in Table 3 is not clear-cut as subset 12 contains 67 out of the 69 DW borrowers. Finally, it is confusing that the abnormal returns for banks not supervised by the Federal Reserve Bank of New York experience significantly positive abnormal returns as opposed to the remaining banks, rejecting the idea that DW borrowers outside New York were easily identified based on the weekly aggregate DW borrowing amounts reported by federal reserve district. One possible explanation may be that, in fact, it is not the location or the Federal Reserve supervisor which explains the positive abnormal return but that other underlying characteristics are the reason. For example, traditional sample banks, for which the average abnormal return is positive, are over-represented outside New York as compared to investment and too-big-to-fail banks, for which the average abnormal return is zero.

To sum up, the Fed's release of detailed DW transaction data on March 31, 2011 did not result in abnormal stock returns on average. One possible reason is that the earlier disclosure of detailed transaction data for all other credit and liquidity programs released the otherwise new, market-sensitive information. However, even if this was true, the DW stigma would not be associated with negative abnormal returns. Crucially, this finding does not stand in contrast to banks' stigmatization in the deposit and interbank markets as shown in the literature (Anbil, 2017; Furfine, 2001, 2003; Armantier et al., 2015), since the comparison is hampered in two regards. First, in my analysis banks' recourse to the DW was not disclosed immediately and, second, unlike creditors or depositors shareholders have a residual claim on a firm's profits and assets. Once an illiquid bank is at the risk of bankruptcy, shareholders have only limited downside[18] but unlimited upside potential. In contrast, deposits and short-term interbank loans are still at risk and depositors and other banks can benefit from reducing their exposure.

While the analysis falls short of pinpointing the exact reason for no or positive abnormal returns, it does not support the idea that DW usage was unveiled within a few trading days upon recourse to the facility. In addition, since banks had access to facilities other than the DW during the financial crisis, the explanation that borrowing under the DW signals superior management skills seems far-fetched. The logic that releasing confidential data by a regulator reduces uncertainty about banks' asset quality, however, is plausible and in line with the findings, especially due to the positive market reaction on the first release on December 1, 2010 but not on the second on March 31, 2011. This backs the story that being able to provide high quality collateral, which was also a prerequisite to receive funds under TAF, during the financial crisis is viewed positively by investors.

The second hypothesis that abnormal returns differ depending on various bank characteristics is neither fully rejected nor accepted. Here, the analysis suffers from the very limited sample size, preventing more elaborated cross-sectional analyses, and potentially omitted variables.

From a methodological perspective, the analysis illustrates the importance of selecting the test statistic and residual and abnormal return generating model. Concerning the test statistic, Appendix B demonstrates that t^{KP} is subdued and less volatile than the other test statistics presented in Subsection 3.3. Consequently and in comparison, the values of t^{KP} throughout the results section can be considered a lower bound, reinforcing the results' robustness. As opposed to the other four test statistics, t^{KP} adjusts for cross-sectional dependence in abnormal returns by scaling with a higher variance estimate. Since the analysis' credibility benefits from extracting as much as possible of the correlation in the residuals (as shown in Kolari and Pynnönen (2010)), choosing the most suitable residual and abnormal return generating model becomes even more important. Therefore, the results in this

[18] The book value of liabilities is likely to exceed the market value of assets so that equity claims are worthless in case of insolvency.

analysis are based on the Six-Factor Model described in Table 1 as it features the highest adjusted R^2, exhibits usually the lowest Mean Squared Prediction Errors[19] and minimizes the cross-sectional dependence in residuals and abnormal returns. Nonetheless, and in order to establish robustness, Tables 5 and 6 in Appendices C and D demonstrate that there is no significant average negative abnormal return on the event day in any of the event studies for DW borrowers independent of the model's specification or estimation window's length.

5 Conclusion

This Master's Thesis examines the question of whether banks should be afraid of adverse effects in equity capital markets if their recourse to the Federal Reserve's (Fed) Discount Window (DW) facility becomes known.

While banks borrowed remarkable amounts from the DW during the financial crisis between 2007 and 2009, the Fed, afraid of stigmatization of DW borrowers, did not reveal details regarding which financial institution borrowed when and how much money against what collateral, citing fears of losing confidence in and between banks. Following a request by Bloomberg News under the Freedom of Information Act and a subsequent court ruling, the Fed was forced to disclose fine-grained DW lending data on March 31, 2011.

The analysis used to answer the research question is based on this unforeseen release and tests for abnormal returns in the borrowing banks' stocks. Although the evidence is not clear-cut, it is reasonable to argue that banks' stocks were not negatively impacted upon disclosing the DW data. Rather, banks seem to benefit as new information about their asset quality enters the market.

This finding is important for a number of reasons. It indicates that the Dodd-Frank Act's requirement to reveal detailed DW lending data after eight quarters does not decrease banks' market capitalization or increase their cost of equity - factors that might otherwise discourage banks to access the DW - and therefore does not constrain the Fed's role as lender of last resort. From this perspective, the policy improves transparency and addresses taxpayers' right to know how much money is lent to whom and under which condition without limiting the central bank's effectiveness to act as lender of last resort. Furthermore, evaluating which central bank tools do and do not work is crucial should another financial crisis occur. In this regard, the analysis suggests that the Fed designed additional credit and liquidity programs successfully as their usage was not associated with negative abnormal stock returns.

[19]The Mean Squared Prediction Errors are calculated in two ways: On the one hand, residuals for trading days 76 to 100 in the estimation window are predicted based on regressions run over the first 75 trading days. On the other, abnormal returns in the event window are predicted based on regressions run over the whole estimation window. Thereafter, the squared difference between the actual values and the respective predictions is averaged and compared for the various models.

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A Variance of Dependent Scaled Abnormal Returns

The derivation roughly follows Kolari and Pynnönen (2010). Asset returns r_{it} of N firms on trading day t are assumed to be serially independently multivariate normally distributed random variables with constant mean and constant covariance matrix for all t (Campbell et al., 1997). Focusing on the setup with a single common event day we can omit the time subscript for sake of readability. Under the null hypothesis we have zero-mean abnormal and scaled abnormal returns which are denoted and calculated as in Section 3. As a consequence, all scaled abnormal returns have the same variance denoted as σ^2. The further notation is defined as follows: μ is the expected value of SAR_i

$$E(SAR_i) = E(SAR) = \mu = 0, \tag{14}$$

σ_{ij} is the covariance between SAR_i and SAR_j

$$E((SAR_i - \mu)(SAR_j - \mu)) = \sigma_{ij} = \sigma_i \sigma_j \rho_{ij} = \sigma^2 \rho_{ij}, \tag{15}$$

and ρ_{ij} is the correlation between SAR_i and SAR_j with an average given by

$$\overline{\rho} = \frac{1}{N(N-1)} \sum_{i=1}^{N} \sum_{\substack{j=1, \\ j \neq i}}^{N} \rho_{ij}. \tag{16}$$

We need to show that

$$s^2(SAR_i) = \frac{1}{N-1} \sum_{i=1}^{N} \left(SAR_i - \frac{1}{N} \sum_{i=1}^{N} \frac{SAR_i}{N} \right)^2 = \frac{1}{N-1} \sum_{i=1}^{N} \left(SAR_i - \overline{SAR} \right)^2 = s^2 \tag{17}$$

is a biased estimator of the variance

$$\sigma^2(SAR_i) = E((SAR_i - E(SAR_i))^2) = E((SAR_i - \mu)^2) = \sigma^2 \tag{18}$$

if scaled abnormal returns are not cross-sectionally independent, i.e., that

$$E(s^2) \neq \sigma^2. \tag{19}$$

We can start by writing $E(s^2)$ as

$$E(s^2) = E\left(\frac{1}{N-1}\sum_{i=1}^{N}\left(SAR_i - \overline{SAR}\right)^2\right) = \frac{1}{N-1}\sum_{i=1}^{N} E\left(\left(SAR_i - \overline{SAR}\right)^2\right), \tag{20}$$

where

$$\begin{aligned} E\left(\left(SAR_i - \overline{SAR}\right)^2\right) &= E\left(\left((SAR_i - \mu) - \left(\overline{SAR} - \mu\right)\right)^2\right) \\ &= E\left((SAR_i - \mu)^2 - 2\left(SAR_i - \mu\right)\left(\overline{SAR} - \mu\right) + \left(\overline{SAR} - \mu\right)^2\right) \\ &= \underbrace{E\left((SAR_i - \mu)^2\right)}_{\text{first term}} - 2\underbrace{E\left((SAR_i - \mu)\left(\overline{SAR} - \mu\right)\right)}_{\text{second term}} + \underbrace{E\left(\left(\overline{SAR} - \mu\right)^2\right)}_{\text{third term}}. \end{aligned} \tag{21}$$

The first term of Equation (21) is equal to the variance

$$E\left((SAR_i - \mu)^2\right) = \sigma^2. \tag{22}$$

The second term of Equation (21) becomes

$$\begin{aligned} E\left((SAR_i - \mu)\left(\overline{SAR} - \mu\right)\right) &= E\left((SAR_i - \mu)\frac{1}{N}\left(\sum_{j=1}^{N} SAR_j - \mu\right)\right) \\ &= \frac{1}{N}\sum_{j=1}^{N} E\left((SAR_i - \mu)(SAR_j - \mu)\right) \\ &= \frac{1}{N}\sum_{j=1}^{N}\sigma_{ij} \\ &= \frac{\sigma^2}{N}\sum_{j=1}^{N}\rho_{ij} \\ &= \frac{\sigma^2}{N}\left(\sum_{j=i}^{N}\rho_{ij} + \sum_{\substack{j=1,\\ j\neq i}}^{N}\rho_{ij}\right) \\ &= \frac{\sigma^2}{N}\left(1 + \sum_{\substack{j=1,\\ j\neq i}}^{N}\rho_{ij}\right). \end{aligned} \tag{23}$$

The third term of Equation (21) can be written as

$$
\begin{aligned}
E\left(\left(\overline{SAR}-\mu\right)^2\right) &= E\left(\left(\frac{1}{N}\sum_{i=1}^{N} SAR_i-\mu\right)^2\right) \\
&= \frac{1}{N^2}\left(\sum_{i=1}^{N} E\left(SAR_i-\mu\right)\right)^2 \\
&= \frac{1}{N^2}\sum_{i=1}^{N}\sum_{j=1}^{N} E\left(\left(SAR_i-\mu\right)\left(SAR_j-\mu\right)\right) \\
&= \frac{1}{N^2}\sum_{j=1}^{N} E\left(\left(SAR_j-\mu\right)\left(SAR_j-\mu\right)\right) \\
&\quad + \frac{1}{N^2}\sum_{j=1}^{N}\sum_{\substack{i=1,\\ i\neq j}}^{N} E\left(\left(SAR_i-\mu\right)\left(SAR_j-\mu\right)\right) \\
&= \frac{1}{N^2}\sum_{j=1}^{N}\sigma^2 + \frac{1}{N^2}\sum_{j=1}^{N}\sum_{\substack{i=1,\\ i\neq j}}^{N}\sigma_{ij} \\
&= \frac{\sigma^2}{N} + \frac{1}{N^2}\frac{N(N-1)}{N(N-1)}\sum_{j=1}^{N}\sum_{\substack{i=1,\\ i\neq j}}^{N}\sigma_{ij} \\
&= \frac{\sigma^2}{N} + \frac{N-1}{N}\frac{\sigma^2}{N(N-1)}\sum_{j=1}^{N}\sum_{\substack{i=1,\\ i\neq j}}^{N}\rho_{ij} \\
&= \frac{\sigma^2}{N} + \frac{(N-1)\sigma^2}{N}\overline{\rho} \\
&= \frac{\sigma^2}{N}(1+(N-1)\overline{\rho}).
\end{aligned} \tag{24}
$$

Using Equations (22), (23), and (24) Equation (21) can be written as

$$
E\left(\left(SAR_i-\overline{SAR}\right)^2\right) = \sigma^2 - \frac{2\sigma^2}{N}\left(1+\sum_{\substack{j=1,\\ j\neq i}}^{N}\rho_{ij}\right) + \frac{\sigma^2}{N}(1+(N-1)\overline{\rho}) \tag{25}
$$

and be plugged into Equation (20)

$$
\begin{aligned}
E(s^2) &= \tfrac{1}{N-1} \sum_{i=1}^{N} \left(\sigma^2 - \frac{2\sigma^2}{N} \left(1 + \sum_{\substack{j=1,\\ j\neq i}}^{N} \rho_{ij} \right) + \frac{\sigma^2}{N}(1+(N-1)\overline{\rho}) \right) \\
&= \tfrac{1}{N-1} \left(N\sigma^2 - \frac{2\sigma^2}{N} \left(\sum_{i=1}^{N} \left(1 + \sum_{\substack{j=1,\\ j\neq i}}^{N} \rho_{ij} \right)\right) + \sigma^2(1+(N-1)\overline{\rho}) \right) \\
&= \tfrac{1}{N-1} \left(N\sigma^2 - \frac{2\sigma^2}{N} \left(\sum_{i=1}^{N} 1 + \sum_{i=1}^{N} \sum_{\substack{j=1,\\ j\neq i}}^{N} \rho_{ij} \right) + \sigma^2(1+(N-1)\overline{\rho}) \right) \\
&= \tfrac{1}{N-1} \left(N\sigma^2 - 2\sigma^2 \left(\frac{N}{N} + \frac{N-1}{N(N-1)} \sum_{i=1}^{N} \sum_{\substack{j=1,\\ j\neq i}}^{N} \rho_{ij} \right) + \sigma^2(1+(N-1)\overline{\rho}) \right) \\
&= \tfrac{1}{N-1} \left(N\sigma^2 - 2\sigma^2\left(1+(N-1)\overline{\rho}\right) + \sigma^2(1+(N-1)\overline{\rho}) \right) \\
&= \tfrac{1}{N-1} \left(N\sigma^2 - \sigma^2\left(1+(N-1)\overline{\rho}\right) \right) \\
&= \tfrac{1}{N-1} \left((N-1)\sigma^2 - \sigma^2(N-1)\overline{\rho} \right) \\
&= \sigma^2 - \sigma^2\overline{\rho} \\
&= \sigma^2(1-\overline{\rho}).
\end{aligned} \tag{26}
$$

Since $E(s^2) \neq \sigma^2$ we have shown that s^2 is a biased estimator of the variance. Equation (26) yields that the variance is given by

$$\sigma^2 = E\left(\frac{s^2}{1-\overline{\rho}}\right). \tag{27}$$

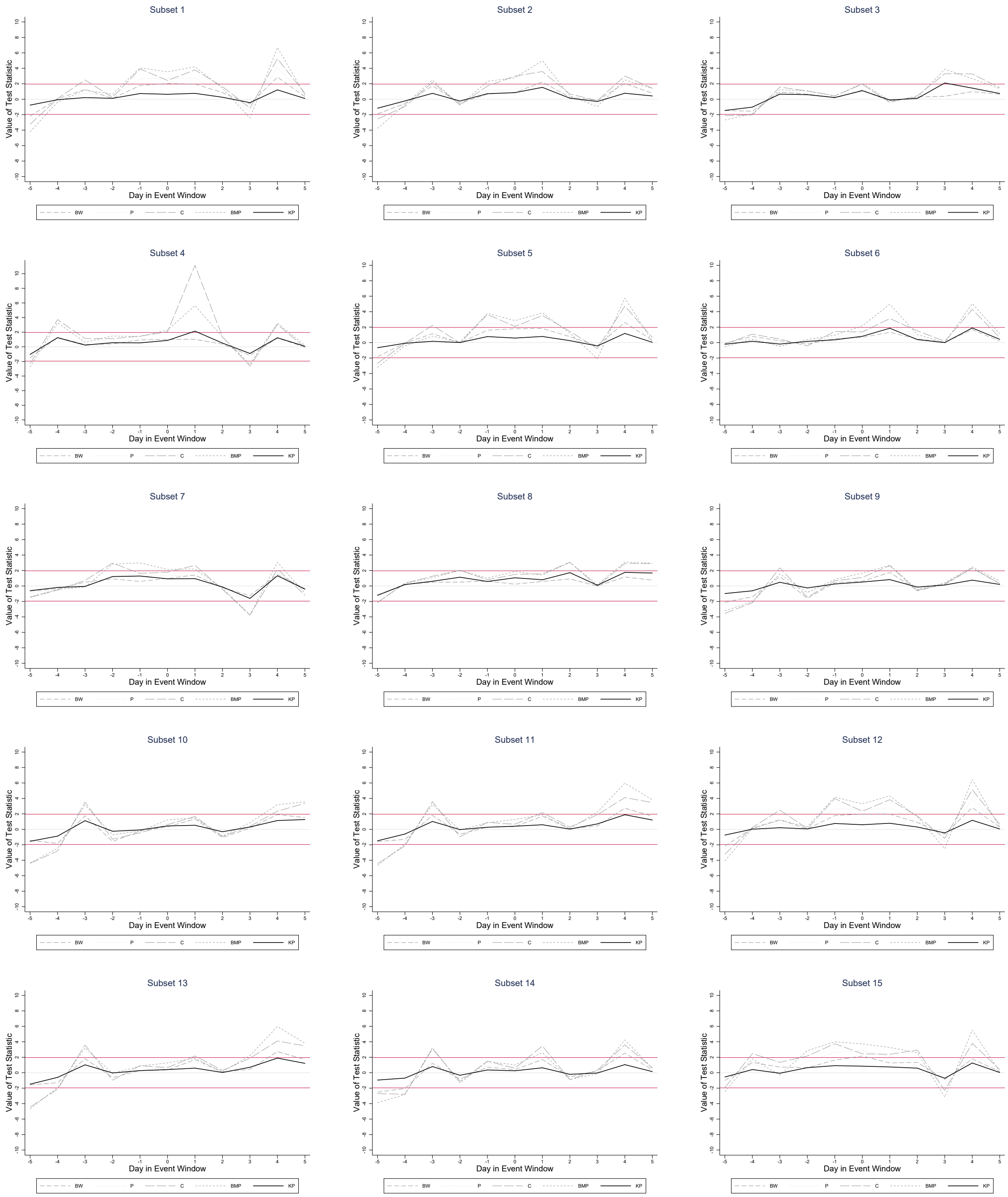
Consequently, an unbiased estimator is

$$s^2_{KP} = \frac{s^2}{1-\overline{r}}, \tag{28}$$

where $\overline{r}$ is the estimated average correlation between scaled abnormal returns.

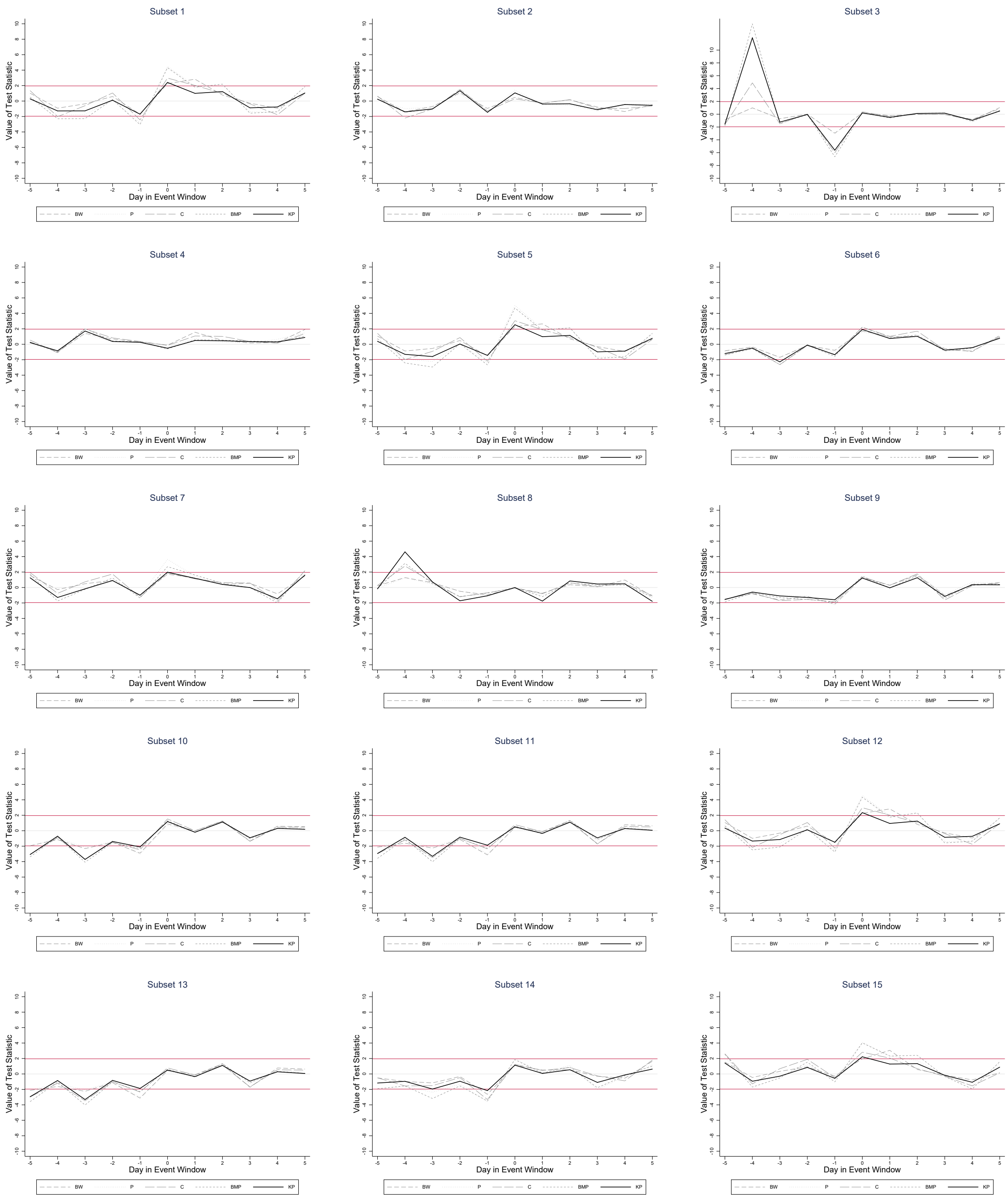
B Evolution of Test Statistics

Figure 2: Values of t-statistics Over Event Window - Event Studies (2)



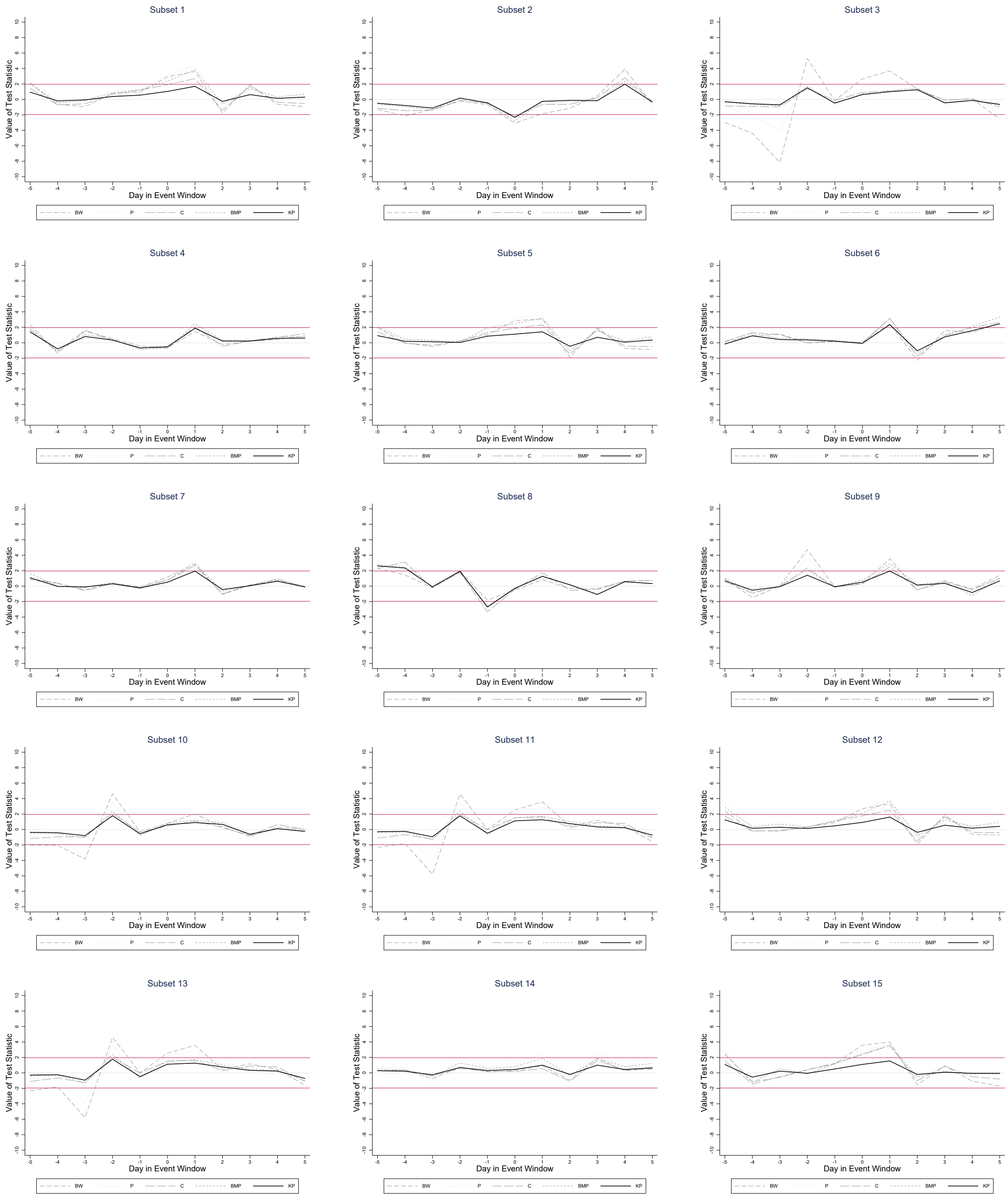
The event date is March 31, 2011 when the Fed released the transaction data for its DW facility. Subsets and t-statistics are described in Section 2 and Subsection 3.3, respectively. Residuals and abnormal returns are estimated based on the Six-Factor Model from Table 1. The horizontal lines represent bounds for the normal distribution's 95% confidence interval.

Figure 3: Values of t-statistics Over Event Window - Event Studies (1)



The event date is December 1, 2010 when the Fed released the transaction data for all its credit and liquidity programs excluding the DW. Subsets and t-statistics are described in Section 2 and Subsection 3.3, respectively. Residuals and abnormal returns are estimated based on the Six-Factor Model from Table 1. The horizontal lines represent bounds for the normal distribution's 95% confidence interval.

Figure 4: Values of t-statistics Over Event Window - Event Studies (3)



The event date varies depending on a given bank's first recourse to the DW or, for the banks in subset 2, to any other of the Fed's credit and liquidity programs. Subsets and t-statistics are described in Section 2 and Subsection 3.3, respectively. Residuals and abnormal returns are estimated based on the Six-Factor Model from Table 1. The horizontal lines represent bounds for the normal distribution's 95% confidence interval.

C Comparison of Models

Table 5: Values of t-statistics - Subset 1

	Event Study (1)		Event Study (2)		Event Study (3)	
t-statistic	$\tau = 0$	$\tau \in [0, 5]$	$\tau = 0$	$\tau \in [0, 5]$	$\tau = 0$	$\tau \in [0, 5]$
Panel A: Mean Model						
BW	7.143*	7.501*	0.447	2.759*	2.453*	2.001*
P	10.081*	9.986*	0.381	3.437*	2.211*	2.691*
C	10.231*	8.453*	0.620	5.789*	1.299	1.128
BMP	12.840*	12.545*	0.572	6.194*	1.510	2.022*
KP	1.767	1.727	0.082	0.884	0.194	0.259
Panel B: Market Model						
BW	1.651	2.783*	0.493	1.583	−0.497	−5.693*
P	3.307*	4.669*	0.596	2.128*	−1.784	−7.054*
C	2.140*	2.053*	0.654	3.090*	−0.273	−4.107*
BMP	3.560*	4.421*	0.817	3.340*	−1.332	−6.741*
KP	0.997	1.239	0.150	0.614	−0.383	−1.937
Panel C: One-Factor Model						
BW	0.399	3.602*	1.162	3.001*	2.367*	1.990*
P	1.049	5.694*	1.538	4.095*	2.299*	3.036*
C	0.602	3.428*	1.515	5.901*	1.447	1.376
BMP	1.177	5.358*	2.057*	6.313*	1.619	2.261*
KP	0.389	1.770	0.376	1.155	0.477	0.666
Panel D: Five-Factor Model						
BW	2.118*	2.741*	2.243*	3.851*	1.992*	1.666
P	4.107*	4.064*	3.015*	5.115*	2.196*	3.073*
C	2.810*	2.336*	2.672*	6.711*	1.533	1.469
BMP	4.009*	3.997*	3.921*	7.795*	1.623	2.522*
KP	2.011*	2.006*	0.704	1.399	0.460	0.715
Panel E: Six-Factor Model						
BW	2.254*	2.312*	2.045*	3.042*	2.923*	2.085*
P	4.477*	3.050*	2.718*	3.774*	3.130*	3.973*
C	2.971*	1.981*	2.433*	5.185*	1.920	1.644
BMP	4.316*	2.948*	3.548*	5.698*	2.354*	3.263*
KP	2.407*	1.644	0.641	1.029	1.035	1.435
Panel F: Industry Model						
BW	1.275	−1.436	1.668	0.457	0.065	−6.065*
P	2.943*	−1.887	2.468*	0.483	−1.109	−7.213*
C	1.635	−1.594	2.216*	0.466	0.044	−4.383*
BMP	3.054*	−1.646	3.384*	0.442	−1.025	−6.686*
KP	1.284	−0.692	0.615	0.080	−0.410	−2.677*

Asterisks indicate significant differences from zero at the 5% level or smaller.

D Change in Estimation Window

Table 6: Values of t-statistics - Subset 1; $T = 300$

	Event Study (1)		Event Study (2)		Event Study (3)	
t-statistic	$\tau = 0$	$\tau \in [0, 5]$	$\tau = 0$	$\tau \in [0, 5]$	$\tau = 0$	$\tau \in [0, 5]$
Panel A: Mean Model						
BW	6.621*	6.865*	0.420	2.654*	3.874*	4.370*
P	9.125*	9.057*	0.471	3.062*	3.592*	5.845*
C	10.176*	8.217*	0.587	5.602*	1.619	2.119*
BMP	12.650*	12.271*	0.714	5.892*	1.978*	3.440*
KP	1.849	1.794	0.099	0.815	0.254	0.441
Panel B: Market Model						
BW	1.543	2.601*	0.509	1.633	−0.642	−7.356*
P	2.920*	4.174*	0.710	2.142*	−2.397*	−8.680*
C	2.140*	2.053*	0.654	3.090*	−0.273	−4.107*
BMP	3.581*	4.343*	0.929	3.261*	−1.528	−6.938*
KP	1.066	1.293	0.221	0.777	−0.445	−2.020*
Panel C: One-Factor Model						
BW	0.193	2.380*	1.094	2.661*	4.269*	5.231*
P	0.844	3.645*	1.421	3.519*	4.069*	7.246*
C	0.311	2.009*	1.356	4.954*	1.984*	2.765*
BMP	1.066	3.721*	1.795	5.265*	2.236*	4.521*
KP	0.354	1.236	0.442	1.295	0.660	1.333
Panel D: Five-Factor Model						
BW	1.594	2.003*	1.466	3.250*	3.537*	5.081*
P	2.493*	3.010*	2.249*	4.755*	3.587*	6.969*
C	2.692*	1.532	1.793	5.899*	2.106*	3.228*
BMP	3.095*	3.195*	2.823*	7.367*	2.241*	4.789*
KP	1.330	1.373	0.734	1.915	0.654	1.397
Panel E: Six-Factor Model						
BW	1.959	1.161	1.317	2.032*	4.993*	5.602*
P	3.297*	1.236	2.053*	2.626*	5.145*	8.512*
C	3.224*	0.815	1.607	3.574*	2.534*	3.233*
BMP	3.945*	1.363	2.559*	3.906*	3.247*	5.812*
KP	2.005*	0.692	0.699	1.066	1.420	2.542*
Panel F: Industry Model						
BW	1.195	−1.346	1.742	0.477	0.085	−7.921*
P	2.489*	−1.670	2.569*	0.512	−1.353	−8.541*
C	1.635	−1.594	2.216*	0.466	0.044	−4.383*
BMP	2.972*	−1.594	3.270*	0.280	−1.033	−6.785*
KP	1.311	−0.703	0.897	0.077	−0.409	−2.686*

Estimation window of 300 days. Asterisks indicate significant differences from zero at the 5% level or smaller.