Bank Cash Holdings and Investor Uncertainty

Benoit d’Udekem

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JEL Classifications: G21, G24, G32.

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Abstract

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1. Introduction

Banking activities involved in generating, monitoring, and trading complex assets and liabilities are by nature information-intensive. The value of bank assets and liabilities and, therefore, banks themselves is driven by market conditions and by the materialization of risks that banks and the market may or may not anticipate and price adequately. Even seemingly simple bank assets and liabilities may lack transparency because of embedded optional features. Opacity, i.e., the uncertainty that investors face in assessing performance and risk due to limited information, is a trait of the banking trade.

Empirically, bank opacity traces primarily to bank-specific assets. Nonetheless, bank assets may not be a concern for investors until a crisis arises (Flannery et al., 2013). When a crisis does arise, more opaque assets may reduce investors’ ability to distinguish between solvent and insolvent banks. This may cause distrust to gain hold and exacerbate systemic risk, with potential adverse consequences for the economy (Jones et al., 2012, 2013). In contrast with more opaque assets, other assets such as treasury bonds, repurchase agreements, and fixed assets are presumed in the banking literature to reduce investor uncertainty. Cash holdings typically also feature prominently in this category.

Do larger cash holdings reduce investor uncertainty? The answer is not clear-cut. Empirical evidence is inconclusive. On one hand, Morgan (2002) observes that larger cash holdings increased bank opacity for US banks between 1983 and 1993, a period that encompasses the savings and loan crisis. On the other hand, Iannotta (2006) demonstrates that liquid assets, including cash, had the opposite effect on bank opacity in Europe between 1993 and 2003. Billett and Garfinkel (2004) contend that larger cash positions may reduce information asymmetry, whereas Wagner (2007b) theorizes that increased asset liquidity is associated with greater risk-taking, which has adverse stability implications during periods of crisis.

Unlike most other bank assets, cash is riskless, and its value is perfectly predictable. Undoubtedly for that reason, cash has often been pooled with other
asset classes presumed to reduce uncertainty. However, large cash holdings may also create uncertainty among investors. First, they can create agency costs, as managers may divert cash to investments that are not in the stockholders’ interests (Jensen, 1986). Second, large cash holdings may reflect precautionary actions taken by management faced with risky cash flows to address potential liquidity shortages and reduce the probability of default (Acharya et al., 2012). In both cases, cash holdings may therefore be associated with uncertainty. In fact, Drobetz et al. (2010) observe that, in unregulated industries, the value of cash holdings is lower when information asymmetry is more significant.

This paper assesses whether, and under what circumstances, cash holdings contribute to stockholder uncertainty. It adopts a novel approach relying on the observation that changes in sell-side analyst “buy-hold-sell” recommendations are more likely to influence stock prices when uncertainty is greater (Loh and Stulz, 2011, 2014; Arand and Kerl, 2012). By measuring the level of influence of analysts, it traces uncertainty to some of its sources or, at least, some of its symptoms. More specifically, I use probit regressions to analyze the extent to which larger cash holdings relative to total assets are associated with a higher (or lower) likelihood that buy-hold-sell recommendation changes will influence bank stock prices. I conduct the analysis over two stressed periods (the financial crisis of 2007-2009 and the ensuing European sovereign debt crisis) and a quiet period in order to gauge the differential influence of cash holdings across three consecutive liquidity and credit regimes. I draw on a sample of nearly 4,000 changes in analyst recommendations relating to 74 listed European banks after excluding recommendations contaminated by firm-related news and events. The sample combines data from Thomson-Reuters I/B/E/S and Bloomberg.

I conclude that large cash positions can be associated with higher or lower uncertainty and that the contribution of cash levels to stockholder uncertainty is primarily driven by liquidity concerns.

During stressed periods, cash holdings may either increase or decrease analyst influence. I further gauge stockholder uncertainty by interacting cash holdings with demandable customer deposits (both as a proportion of total as-
During the financial crisis of 2007-2009, a combination of lower cash holdings and larger customer deposits is associated with a higher degree of stockholder uncertainty. In such circumstances, deposit demandability exposes banks to liquidity risks. Also, a combination of significant cash holdings and low customer deposits is associated with heightened uncertainty among stockholders. A possible explanation is that stockholders are worried about the agency costs of free cash flows. This hypothesis is consistent with Acharya et al. (2011), who suggest that banks may have incentives during crises to hold liquid assets in order to purchase assets from other failing banks at fire sale prices. The opacity of such transactions and the purchased assets may unnerve stockholders. Another explanation may be that cash holdings reflect a precautionary stance adopted by management in the presence of heightened default risk (Acharya et al., 2012). In turn, the imbalance between short-term liquid assets and liabilities may create stockholder anxiety. Consistent with this second explanation, Cornett et al. (2011) provide evidence that the US banks hoarding liquid assets during the financial crisis were the ones with greater exposure to liquidity risk. In contrast, the combination of lower (higher) relative customer deposits and lower (higher) cash holdings is not associated with greater uncertainty. Stockholders appear to find comfort in larger liquidity buffers, provided they are proportionate to potential debtholder claims, which is consistent with the contention of Billett and Garfinkel (2004).

During 2009-2012, a period of monetary and banking uncertainty in the eurozone, both larger cash holdings and larger customer deposit positions relative to assets reduce investor uncertainty. In this case, interacting cash holdings with customer deposits brings no additional insight. Stockholders appear to be reassured by the presence of larger liquidity buffers. This observation may also relate to the growing dichotomy between sounder banks, amassing deposits and cash, and weaker ones, experiencing deposit flight. This would also lend support to the contention of Billett and Garfinkel (2004) that larger cash positions may reduce information asymmetry. However, the period is also characterized
by significant deposit migration from seemingly weaker to seemingly stronger banks. Larger cash and deposit levels may thus be a sign of greater perceived bank soundness rather than a way for banks to reduce information asymmetry.

Outside of crisis periods, cash holdings at first do not appear to be associated with higher uncertainty among stockholders, who seem to find cash holdings as “boring” as other banking assets, as observed by Flannery et al. (2004). However, after controlling for credit risk through credit ratings, a pattern similar to the one observed during the financial crisis emerges. This suggests that bank stockholders may be as sensitive to liquidity risk and vigilant to the balance between cash holdings and deposits during non-crisis periods as during crises, giving indirect empirical support to the contention that investors monitor bank risk-taking and depositor behavior.

The paper contributes to our understanding of overall bank opacity. In particular, it demonstrates the relevance of cash holdings to bank stockholders. It also reconciles theory and empirical evidence that may have appeared contradictory, including the inconclusive findings of Morgan (2002) and Iannotta (2006) on the contribution of cash holdings to bank opacity, the conclusion of Flannery et al. (2004, 2013) that the market may not be concerned by bank assets outside of a crisis period, the contention of Billett and Garfinkel (2004) that larger cash positions may reduce information asymmetry, and the theory of Wagner (2007b) that greater asset liquidity may contribute to fragility, which translates to greater investor uncertainty. Finally, it suggests that additional market disclosure about liquidity may help investors better appreciate bank liquidity risks.

The paper bridges several strands of literature. Primarily, it connects the corporate finance literature on cash holdings, which usually excludes financial institutions from its scope, and the literature on bank liquidity. According to the former, notably Opler et al. (1999) and Acharya et al. (2012), larger cash holdings reflect precautions taken by management to preserve access to capital markets in spite of riskier cash flows or higher credit risk for investors. According to the latter, notably Calomiris and Kahn (1991) and Flannery (1994), investors
have an incentive to monitor their banks’ risk-taking and to take action if it exceeds their appetite. However, monitoring of incentives may be reduced by the presence of deposit insurance and is hindered by the greater opacity of banking institutions. Cash holdings are considered appropriate ways of reducing information asymmetry (Billett and Garfinkel, 2004), absorbing liquidity shocks (Ratnovski, 2013) and reducing risk-taking incentives (Calomiris et al., 2012). Secondarily, the paper relies on recent findings in the analyst literature and identifies new factors that are associated with a greater influence of sell-side analysts on stock prices, beyond those that were tested by Loh and Stulz (2014).

The paper is structured as follows: Section 2 briefly reviews relevant literature and presents the paper’s two hypotheses. Section 3 describes the data set and documents the steps taken to trace uncertainty, measured as relative analyst influence, to its sources. Section 4 examines whether cash is associated with higher or lower stockholder uncertainty, first on its own and second in relation to demandable customer deposits, in order to test the paper’s hypotheses. Section 5 uses additional controls to confirm the robustness of the paper’s findings. Section 6 presents the conclusions.

2. Related Literature and Hypothesis Development

2.1. Cash Holdings and Investor Uncertainty

The financial crisis of 2007-2009 shows the extent to which banks and the banking system as a whole can be exposed to asset bubbles. When these bubbles pop, banks, including hitherto apparently healthy ones, may fail unexpectedly. If allowed to fail, banks may expose the global financial industry to systemic risk. If, instead, they are bailed out, banks expose governments to additional debt burdens that may become excessive.

In addition to the bubbles themselves, intrinsic opacity makes it difficult for investors to assess bank soundness. Opacity may therefore magnify the impact of asset bubbles. There is broad empirical support for the contention that, when information is in limited supply, stockholders infer value changes from
what other banks may disclose. Recurrent bad news may cause distrust to set in and volatility to increase (Szafarz, 2012). In the worst case, the whole system may go into a tailspin and require public authorities to intervene in order to prevent the system from collapsing.

Bank assets are shown in the literature to be the main source of opacity. Loans, the primary assets of most banks, are opaque because lending activities (including granting, monitoring, and collection) rely on substantial amounts of privileged information about granular borrowers. The cost of producing such information and the need for additional investor services justify the existence of financial intermediaries. In contrast, trading assets are assumed to be opaque, not because they require the processing of large amounts of privileged information, but because they are transient (Morgan, 2002). Bank trading positions change so often (if not constantly) that they cannot be adequately monitored by investors. Interestingly, trading activities may be associated with large cash levels resulting from the settlement or closure of positions. Nonetheless, opaque bank assets may only be concerns for investors in stressed times. It is only during periods of crisis that the greater opacity of banking assets has been shown to translate to stock market metrics evidencing greater opacity (Flannery et al., 2004, 2013). Even so, identification of banking asset classes associated with market uncertainty remains elusive.

The issue of greater asset opacity is magnified by several factors. First, bankers may have incentives to invest in more opaque assets because these assets may generate higher returns (Jones et al., 2013), or simply because bankers value opacity (Wagner, 2007a). Greater opacity may therefore be a byproduct of competitive pressure or financial development. Second, by nature, accounting processes aggregate information. At each stage of aggregation, granular information is lost and transparency decreases. At the most aggregated levels typically presented in financial statements, it may be difficult for outsiders to assess bank soundness (Genay, 1998). Third, accounting processes may not be able to keep pace with market conditions, causing financial information to be out of date by the time it is published. Also, complex assets may be so diffi-
cult to value that disclosures may appear untimely or inadequate (Vyas, 2011). Bank health may be all the more difficult to assess if financial information is not up to date. Fourth, bankers may be biased against transparency on competitive grounds (Hyytinen and Takalo, 2002). Also, in adverse market circumstances bankers may fear that negative information could adversely affect their access to credit markets. They may therefore seek to delay negative news, hoping that the situation will improve.

In contrast with loans and trading assets, certain assets and liabilities are assumed to reduce opacity. Cash is often categorized with these assets, on the grounds that cash is a riskless asset and that its value is always observable (Calomiris et al., 2012). Cash holdings are also presumed to mitigate information asymmetry and increase financial flexibility, measured as the cost of accessing insured and uninsured deposit markets (Billett and Garfinkel, 2004).

However, greater opacity arguably subjects the banking industry to more significant agency risks than other industries. Behind the veil of complex disclosures, bankers may make risky asset bets and expose liability and equity holders to risks that even the most discerning investors may not expect. The agency costs of free cash flows identified by Jensen (1986) may be significant in banks. Such is the explanation advanced by Morgan (2002) for his observation that larger cash holdings increase bank opacity. In fact, outside of regulated industries, Drobetz et al. (2010) show that investors discount cash holdings as information asymmetry increases. They conclude that when information asymmetry is significant, the agency costs of free cash flows exceed the benefits of maintaining large cash balances to finance new undertakings.

While cash holdings are riskless and provide greater predictability, they may originate from opaque risk-taking activities. They also create agency risks magnified by the greater opacity of banks. This reasoning leads to my first hypothesis:

**Hypothesis 1:** Large cash holdings relative to assets may increase investor uncertainty.
2.2. Cash Holdings and Liquidity Risk

The financial crisis of 2007-2009 exposed the interrelationship between liquidity, solvency, and opacity. In certain cases, greater opacity prevented liability holders from assessing the financial health of their counterparties. Fear of insolvency, rather than looming insolvency, was enough to create significant liquidity issues for certain banks (Huang and Ratnovski, 2011). The problem was particularly acute in wholesale funding markets, although a number of banks also experienced runs on deposits.

Demandable deposits expose bankers to the sudden withdrawal of funding, with potentially disastrous consequences. As such, demandable deposits are theorized to be an effective way to rein in management risk-taking (Calomiris and Kahn, 1991; Flannery, 1994). Substantial empirical evidence lends support to this theory. Depositors are served in sequential order when they withdraw their deposits. Larger depositors have an incentive to monitor their banks’ risk-taking and to be among the first to run or to renegotiate the terms of their deposits with bankers if risk-taking exceeds their appetite. Similarly, the financial crisis demonstrated that wholesale funding markets are also subject to runs (Goldsmith-Pinkham and Yorulmazer, 2010; Gorton and Metrick, 2012) and may also expose banks to potential “sudden death”.

Cash holdings are the counterpart and act as a guarantee of liability holder demands. Cash in limited supply may create concerns among investors if demandable deposits are significant or if a bank is heavily reliant on wholesale funding. Liquidity buffers may reassure investors and induce greater management prudence (Billett and Garfinkel, 2004; Calomiris et al., 2012; Ratnovski, 2013).

Alternatively, large cash positions may reflect actions by management to buttress a bank’s liquidity position. As such, liquidity buffers exceeding levels warranted to meet liability holder demands may be evidence of either prudence or nervousness of management faced with potential or impending liquidity issues. Acharya et al. (2012) observe outside the financial sector that firms closer to distress are more likely to maintain larger cash buffers. Also, Cornett et al.
find that, during the financial crisis of 2007-2009, banks holding more illiquid asset portfolios increased their liquidity buffer and reduced lending. Alternatively, Acharya et al. (2011) contend that, during crises, seemingly precautionary cash positions may in fact be war chests created to purchase assets from other failing banks at fire sale prices. Similarly, Wagner (2007b) advances that increased asset liquidity may induce excessive risk-taking during crisis periods, leading to greater bank fragility and lower overall systemic stability. Apparent management prudence may actually hide opportunistic motives that may unnerve investors. As a consequence, the uncertainty created by concerns over liquidity may be difficult to clearly dissociate from the uncertainty created by agency risks.

Liquidity may be a life-threatening issue for banks. Cash holdings, as the counterpart of liability holder demands, may either be reassuring or worrisome to investors, depending on circumstances. This reasoning leads to my second hypothesis:

Hypothesis 2: Greater investor uncertainty associated with bank cash holdings reflects heightened liquidity concerns.

3. Empirical Methodology and Data

There is substantial empirical support in the analyst forecasting literature for the contention that analyst opinions and recommendations are more likely to impact stock prices when uncertainty increases (Loh and Stulz, 2011, 2014; Arand and Kerl, 2012). Firm-specific factors connected with uncertainty, including smaller firm size, a firm’s growth profile and greater dispersion of analyst earnings forecasts, are associated with greater analyst influence. Similarly, analyst informativeness is shown to be greater in uncertain environments characterized by greater volatility. Finally, analyst influence is more significant during periods of uncertainty, an observation consistent with results presented below. Changes in analyst influence thus reflect changes in levels of investor uncertainty.

The empirical approach developed by Loh and Stulz (2011) provides an em-
pirical framework for tracing uncertainty to some of its sources or, alternatively, detecting some of its symptoms. More specifically, it attempts to determine the likelihood that changes in security analyst buy-hold-sell recommendations\textsuperscript{2} will be associated with measurable changes in stock prices, i.e., abnormal returns. It then identifies the factors that may affect this likelihood, such as the characteristics of brokers or security analysts, the characteristics of the recommendations, and stock trading metrics. When applied to a large sample of US firms, this approach confirms many prior empirical findings documented in the analyst forecasting literature. For example, it shows that recommendation changes are more likely to be influential when new recommendations differ markedly from the consensus (the “average” view of analysts) or when they are issued by influential analysts. It also shows that few analyst recommendation changes (approximately 12\% in their sample) impact stock prices.

The present paper uses analyst influence as a proxy for investor uncertainty, after controlling for the firm and analyst environments. It tests whether cash holdings affect the likelihood that changes in security analyst recommendations will influence stock prices. More specifically, it incorporates accounting data and credit risk measurements in probit regressions of analyst influence, as described in Section 3.2. The sample of nearly 4,000 recommendation changes, relating to 74 listed European banks and spanning two stressed periods and one quiet period, makes it possible to gauge the differential influence of cash holdings across different macroeconomic and uncertainty regimes, as described in Section 3.1.

3.1. Sample

The paper focuses on European banks that have both actively traded, liquid stock and sustained analyst following. Significant liquidity ensures that new information is quickly impounded in stock prices (Chung and Hrazdil, 2010). Sustained analyst following ensures the timeliness and relevance of analyst rec-

\textsuperscript{2}Henceforth referred to synonymously as “analyst influence”.
ommendations.

The banks included in major stock market indexes typically meet such requirements. The sample therefore comprises all banking institutions included in the STOXX Europe 600 Banks index\(^3\) at any time since July 1, 2004, for a total of 88 banks from 17 European countries. Changes to indexes often reflect significant events such as acquisitions, demergers, bankruptcies, or major business shifts. By construction, the sample mitigates survivorship bias.

For all banks in the sample, I collect daily closing prices and dividends paid from Bloomberg. I collect Standard & Poor’s, Moody’s and Fitch credit rating histories for each bank from Bloomberg\(^4\) and map credit ratings on a numerical scale from 1 (AAA/Aaa) to 19 (CCC-/Caa3). Separately, I also collect analyst recommendations from the Thomson-Reuters Institutional Brokers Estimate System (I/B/E/S) International Historical Detail File database. I match the two data sets using the bank SEDOLs, which reduces the sample to 84 bank stocks,\(^5\) corresponding to 15,081 recommendations issued between January 1, 2004 and June 30, 2012. I also collect index prices directly from STOXX,\(^6\) exchange rates from the European Central Bank,\(^7\) and market and accounting data from Bloomberg.\(^8\) For consistency with prior related research, cash hold-

\(^3\)STOXX Europe 600 Banks is one of the most representative banking indexes in Europe. STOXX Europe 600 Banks is a subset of the STOXX Europe 600 Index including all companies categorized as “Banks” in FTSE’s Industry Classification Benchmark (ICB). STOXX Europe 600 was created in 1991 and is one of the most comprehensive European indexes, with 600 components at all times. STOXX Europe 600 includes small, mid and large caps in equal proportion (200 each) from all industries across 18 Western European countries, including all core eurozone countries, the United Kingdom, and all Nordic countries.

\(^4\)Specifically, for listed entities, the Fitch and Moody’s unsecured senior debt ratings and the Standard & Poor’s long-term foreign issue ratings or, in the few cases where they are assigned to a bank held by a listed bank holding company, those ratings plus one, as consistent with the policies of the credit rating agencies.

\(^5\)The excluded banks, including two listed central banks, have no regular analyst following over the period.

\(^6\)See http://www.stoxx.com/data/historical/historical_benchmark.html

\(^7\)See http://www.ecb.int/stats/exchange/eurofxref/html/index.en.html

\(^8\)Data in the following fields: BS_TOT_ASSET (total assets),
ings are those reported by banking institutions in financial statements. The same principle applies to the other accounting variables.

Appendix A summarizes the steps taken to calculate recommendation changes and the associated abnormal returns. Processing recommendations and excluding those contaminated by firm-specific news and events yields a sample of 4,501 changes in analyst recommendations for 80 banks. The average (median) cumulative abnormal return for the full sample is -0.03% (-0.04%), very close to 0. Only 7.44% of the recommendation changes influence bank stock prices. Combining the sample with accounting data causes sample size to drop to 3,960 observations and the proportion of influential recommendations to increase slightly, to 7.6%. Table 2 provides sample statistics.

Mody and Sandri (2012) break the eurozone sovereign and banking crisis down into three phases. They place the beginning of the subprime crisis in July 2007, when both sovereign and bank spreads showed signs of stress, and they find evidence of a “regime change” characterized by intertwined financial and sovereign shocks beginning in January 2009, with the nationalization of Anglo Irish Bank. Accordingly, for the purpose of this analysis, the quiet (“pre-crisis”) period is considered to run from January 1, 2004 to June 30, 2007; the crisis (“financial crisis”) period, from July 1, 2007 to December 31, 2008, and the resolution (“post-crisis”) period, from January 1, 2009 to June 30, 2012.

Table 2 shows that the level of analyst influence varies over the course of the three periods. Before the crisis, 8.6% of analyst recommendation changes are influential. Analysts become more influential during the financial crisis, with the percentage of influential recommendations increasing to 9.7%, which is consistent with the observations of Loh and Stulz (2014). Analysts become less influential after the crisis, with only 6.0% of recommendation changes being

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CASH_TO_TOT_ASSET (cash-to-total assets), BS_CUSTOMER_DEPOSITS (bank deposits), COM_EQY_TO_TOT_ASSET (common equity-to-total assets), RETURN_COM_EQY (ROE), CUR_MKT_CAP (market capitalization), and MARKET_CAPITALIZATION_TO_BV (market-to-book value of equity).

Excluding 605 reaffirmations of previous analyst recommendations.
Table 1: Definition of variables used in regressions. Accounting variables are those reported by the bank in its most recent financial statements. Market and other variables are measured on the recommendation date.

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>INFLUENTIAL_RET</td>
<td>Binary variable indicating if a change in analyst recommendation influenced a bank’s stock price.</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Bank characteristics</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>CASH/ASSETS</td>
<td>Ratio of cash holdings to total assets</td>
</tr>
<tr>
<td>DEPOSITS/ASSETS</td>
<td>Ratio of total deposits to total assets</td>
</tr>
<tr>
<td>EQUITY/ASSETS</td>
<td>Ratio of total equity to total assets</td>
</tr>
<tr>
<td>ROE</td>
<td>Return on Equity</td>
</tr>
<tr>
<td>LOG_BM</td>
<td>Natural logarithm of book-to-market value of equity</td>
</tr>
<tr>
<td>LOG_SIZE</td>
<td>Natural logarithm of market capitalization (converted to EUR as necessary)</td>
</tr>
<tr>
<td>LOG_ASSETS</td>
<td>Natural logarithm of total assets (converted to EUR as necessary)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Broker and Analyst Controls</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>FOLLOWED_FIRMS</td>
<td>Measure of a broker’s breadth of coverage, based on the percentage of STOXX Europe 600 companies covered by the broker between January 1, 2004 and June 30, 2012</td>
</tr>
<tr>
<td>INFL_ANALYST_RET</td>
<td>Binary variable is set to 1 if an analyst has been influential previously for any stock and to 0 otherwise</td>
</tr>
<tr>
<td>INFL_ANALYST_STOCK_RET</td>
<td>Binary variable is set to 1 if an analyst has been influential previously for the recommended stock and to 0 otherwise</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Recommendation and Market Controls</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>IRECCD</td>
<td>Recommendation level (on a scale from 1 [strong sell] to 5 [strong buy]) after a recommendation revision</td>
</tr>
<tr>
<td>DIFF_CONSENSUS</td>
<td>Absolute value of the difference between the new recommendation level and the mean recommendation consensus level</td>
</tr>
<tr>
<td>PERF</td>
<td>Difference between a bank’s aggregated daily log return and that of the STOXX Europe 600 Index over a period of 90 days ending six days before the recommendation is made</td>
</tr>
<tr>
<td>VOLAT</td>
<td>Difference between a bank’s standard deviation of daily log returns and that of the STOXX Europe 600 Index over a period of 90 days ending six days before the recommendation is made</td>
</tr>
<tr>
<td>SD_REC</td>
<td>Standard deviation of analyst recommendations prior to the recommendation change</td>
</tr>
<tr>
<td>VIX</td>
<td>Value of the VIX Index on the recommendation date</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Credit Risk Controls</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>LOWEST_RATING</td>
<td>Lowest alphanumeric credit rating assigned to a bank by Standard &amp; Poor’s, Moody’s or Fitch (on a scale from 1 [AAA/Aaa] to 19 [CCC-/Caa3])</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Robustness Checks</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>RATING_SPLIT</td>
<td>Largest difference between the credit ratings assigned to a bank by Standard &amp; Poor’s, Moody’s or Fitch (on the credit rating scale from 1 [AAA/Aaa] to 19 [CCC-/Caa3])</td>
</tr>
<tr>
<td>NUM_RATINGS</td>
<td>Number of credit ratings attributed independently by Standard &amp; Poor’s, Moody’s or Fitch</td>
</tr>
</tbody>
</table>
Table 2: Statistics for the sample of recommendation changes and period subsamples. N is the total number of observations. “% Full sample” is the number of observations in each subsample as a percentage of the number of observations in the full sample. “% Influential” is the percentage of recommendation changes that influence stock prices. “# Banks” is the number of different banks. “# Countries” is the number of different countries in which banks are headquartered. “Avg Bank/Country” is the average number of banks per country. “Min (Max) Bank/Country” is the smallest (largest) number of banks per country. “# Brokers” is the number of different brokers. “# Analysts” is the number of different analysts.

<table>
<thead>
<tr>
<th>Period start</th>
<th>Full sample</th>
<th>Pre-crisis</th>
<th>Financial crisis</th>
<th>Post-crisis</th>
</tr>
</thead>
<tbody>
<tr>
<td>N</td>
<td>3,960</td>
<td>1,365</td>
<td>804</td>
<td>1,791</td>
</tr>
<tr>
<td>% Full sample</td>
<td>100%</td>
<td>34.5%</td>
<td>20.3%</td>
<td>45.2%</td>
</tr>
<tr>
<td>% Influential</td>
<td>7.6%</td>
<td>8.6%</td>
<td>9.7%</td>
<td>6.0%</td>
</tr>
<tr>
<td># Banks</td>
<td>74</td>
<td>61</td>
<td>58</td>
<td>55</td>
</tr>
<tr>
<td># Countries</td>
<td>17</td>
<td>17</td>
<td>17</td>
<td>15</td>
</tr>
<tr>
<td>Avg Bank/Country</td>
<td>4.35</td>
<td>3.59</td>
<td>3.41</td>
<td>3.67</td>
</tr>
<tr>
<td>Min Bank/Country</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Max Bank/Country</td>
<td>17</td>
<td>13</td>
<td>10</td>
<td>10</td>
</tr>
<tr>
<td># Brokers</td>
<td>173</td>
<td>117</td>
<td>98</td>
<td>133</td>
</tr>
<tr>
<td># Analysts</td>
<td>636</td>
<td>349</td>
<td>262</td>
<td>363</td>
</tr>
</tbody>
</table>
3.2. Regression Specification and Variables

In order to assess the sources of variations in analyst influence, translating stockholder uncertainty, I estimate probit regressions in which the likelihood that a recommendation will be influential is the explained variable, and the bank characteristics and control variables connected to my two hypotheses are the dependent variables:

\[
P(\text{Infl} = 1 \mid X, C) = \Phi(a + b \times X' + c \times C')
\]  

(1)

where \(P\) is the probability operator, \(\text{Infl}\) is a vector of binary variables indicating whether each individual recommendation has had an influence, \(\Phi\) is the cumulative distribution function of the standard normal distribution, \(X\) is a vector with the bank characteristics to be tested, \(C\) is a vector with the control variables, and \(a, b\) and \(c\) are the regression parameters to be estimated.

For bank characteristics to be associated conclusively with higher or lower uncertainty, they must be statistically significant. The absence of statistical significance suggests that bank characteristics or control variables have an ambiguous effect and that no firm conclusion can be drawn. In order for sources of uncertainty to be comparable across banks of different sizes, accounting variables are deflated by total assets. Also, in order to address potential causality issues, accounting variables are included only after they have been disclosed by banks.

The main accounting variables connected with the paper’s two hypotheses are cash holdings (CASH_TO_ASSETS) and deposits (DEPOSITS_TO_ASSETS). Other accounting variables relevant for control purposes include measurements

\footnote{In unreported results, I observe that analysts who were previously influential also lose most of the incremental influence they had gained. The financial crisis appears to have affected analyst influence, possibly because they lost credibility during it. This merits further investigation clearly beyond the scope of this paper.}
of relative profitability (ROE) and leverage (EQUITY_TO_ASSETS). Although intuition dictates that more equity should be associated with lower bank opacity, there are conflicting results in prior empirical literature on this issue.

Loh and Stulz (2011) find both a growth (versus value) and a size effect on analyst influence. Analysts are shown to be less influential on larger firms and those with a high book-to-market because of the lower uncertainty that such firms present. In particular, firm size is identified with the breadth of the firm’s information environment. Accordingly, the regressions control for size, taking the natural logarithm of a bank’s market capitalization converted to EUR at prevailing exchange rates (LOG_SIZE) and the natural logarithm of the book-to-market (B/M) ratio (LOG_BM).

The literature finds that size, like leverage, has an inconclusive impact on relative bank opacity. In fact, size may have opposing effects on stockholder uncertainty. On the one hand, diversification increases with size, and exposure to idiosyncratic risks becomes less of a concern for investors (Dermine and Schoenmaker, 2010). On the other hand, banks become more complex as they increase in size, and more difficult for investors to understand. Morgan (2002) observes that “size may be a two-edged sword for the [credit rating] analysts: bigger banks may be better diversified, meaning less concern about the idiosyncratic risks at each bank, but greater size also means [credit rating] analysts must consider managers' ability to cope with more complex, less focused operations”.

Unlike Loh and Stulz (2011), Jones et al. (2012) find that bank opacity increases, rather than decreases with the B/M ratio. However, the B/M ratio may have a different meaning in banking than in other industries. Huizinga and Laeven (2011) posit that Tobin’s q reflects the implicit premium or discount applied by the market to a bank’s assets, over and above the fair value reported in its financial statements. Equivalently, a larger B/M ratio can be interpreted as assets being discounted more significantly by stockholders.

The regressions also control for possible extra influence exerted by some analysts or brokers. They test whether the fact that an analyst has been influential in the past increases the likelihood that he/she may be influential in the fu-
ture (previous influence on any stock (INFL_ANALYST_RET) or on the same stock (INFL_ANALYST_STOCK_RET)). Boni and Womack (2006) report that broader industry coverage by brokers should translate into more influential aggregate recommendations. Broker coverage should therefore contribute to the influential character of recommendations. Consequently, another control is the breadth of broker coverage (FOLLOWED_FIRMS), determined empirically as the percentage of companies covered by a broker out of a sample of the 971 companies included in the STOXX Europe 600 Index since January 1, 2004.11

Other control variables include market- and recommendation-related variables as well as relative uncertainty. The regressions control for recommendation levels after recommendation changes (IRECCD) and the absolute difference between a new recommendation and the mean recommendation consensus (DIFF_CONSENSUS), for recent volatility (VOLAT) and performance (PERF);12 and for the relative level of uncertainty (by taking the standard deviation of analyst recommendation levels (SD_REC)).

Lastly, the latter regressions stress test for credit risk, using two measurements, as well as for a proxy of opacity commonly reported in the literature. First, the regressions incorporate the lowest rating assigned to a bank by Standard & Poor’s, Moody’s or Fitch, on a scale from 1 (AAA/Aaa) to 19 [CCC/Caa3] (LOWEST_RATING). If the observed uncertainty was due to credit risk, incorporating credit ratings in the regressions should reduce the value or the significance of the tested accounting variables, as in Acharya et al. (2012). Second, they incorporate the VIX Index to control for market-wide volatility. Third, following prior literature, the regressions include credit rating splits, that is, the largest difference between the credit ratings assigned to a bank by Standard & Poor’s, Moody’s or Fitch.

11In unreported results, I confirm empirically that larger brokers, and in particular bulge bracket investment banks, have much broader firm coverage than the other brokers.
12Measured, respectively, as the standard deviation of regression residuals and the difference between the absolute return of a stock less the absolute return of the STOXX Europe 600 Index over the 90 calendar-day estimation window used in the three-factor model.
Table 1 defines all regression variables. Table 3 provides summary statistics for all of the above variables for the full period between January 1, 2004 and June 30, 2012. Table 4 provides the same information for the three sub-periods.

The summary statistics show that the sample includes banks with diverse capital structures and business models. The panel banks fund themselves in different ways. Deposits range from virtually zero to 83% of total assets. The banks report cash balances between 2% and 18.3% of total assets. Interestingly, average and median cash holdings increase markedly after the financial crisis. The interquartile range of return on equity is in line with what an average bank would be expected to report in the absence of stress: between 6.8% and 17.9%. Nonetheless, average and median profitability decrease significantly after the financial crisis, while the average log book-to-market becomes positive and balance sheet sizes diminish.

The average and median credit ratings are 5.70 and 6.0 respectively, i.e., near the A/A2 level (Standard & Poor’s, Fitch and Moody’s). Credit ratings range from 2.0 (AA+/Aa1) to 18.0 (CCC/Caa2), with the lowest ratings being attributed to Greek banks during the eurozone crisis. Credit rating agencies are generally in broad agreement, with average and median rating splits at 1.37 and 1.0, respectively, and a standard deviation of rating splits close to 1.0. Nonetheless, the rating splits (average and median credit ratings) are higher (lower) than those reported by Iannotta (2006) over the 1993-2003 period (0.53 for rating splits and 2.26 for average credit ratings). A likely explanation is that the ratings reported here are for banks and not the individual bonds they issue. Higher rated banks presumably access the market more often than lower rated banks. Also, they are less often subject rating splits. Interestingly, average and median ratings decrease during the financial crisis, although rating splits also diverge during that period. Rating splits thus show a pattern similar to analyst influence during an acute crisis, though they do not recede to pre-crisis levels after the crisis.
Table 3: Summary statistics for regression variables. All variables are defined in Table 1. As their name implies, balance sheet items are deflated by total assets.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Min</th>
<th>25%</th>
<th>Median</th>
<th>75%</th>
<th>Max</th>
<th>Std Dev</th>
</tr>
</thead>
<tbody>
<tr>
<td>INFLUENTIAL_RET</td>
<td>0.076</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>1.000</td>
<td>0.265</td>
<td></td>
</tr>
<tr>
<td>CASH_TO_ASSETS</td>
<td>0.020</td>
<td>0.000</td>
<td>0.006</td>
<td>0.011</td>
<td>0.027</td>
<td>0.183</td>
<td>0.020</td>
</tr>
<tr>
<td>DEPOSITS_TO_ASSETS</td>
<td>0.380</td>
<td>0.025</td>
<td>0.285</td>
<td>0.372</td>
<td>0.466</td>
<td>0.830</td>
<td>0.134</td>
</tr>
<tr>
<td>EQUITY_TO_ASSETS</td>
<td>0.049</td>
<td>0.005</td>
<td>0.033</td>
<td>0.048</td>
<td>0.062</td>
<td>0.156</td>
<td>0.020</td>
</tr>
<tr>
<td>ROE</td>
<td>0.112</td>
<td>-0.626</td>
<td>0.068</td>
<td>0.129</td>
<td>0.179</td>
<td>0.424</td>
<td>0.119</td>
</tr>
<tr>
<td>LOG_BM</td>
<td>-0.179</td>
<td>-2.033</td>
<td>-0.629</td>
<td>-0.271</td>
<td>0.203</td>
<td>2.121</td>
<td>0.620</td>
</tr>
<tr>
<td>INFL_ANALYST_RET</td>
<td>0.389</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>1.000</td>
<td>1.000</td>
<td>0.488</td>
</tr>
<tr>
<td>INFL_ANALYST_STOCK_RET</td>
<td>0.101</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>1.000</td>
<td>1.000</td>
<td>0.301</td>
</tr>
<tr>
<td>FOLLOWED_FIRMS</td>
<td>0.321</td>
<td>0.002</td>
<td>0.077</td>
<td>0.197</td>
<td>0.602</td>
<td>0.859</td>
<td>0.279</td>
</tr>
<tr>
<td>PERF</td>
<td>-0.026</td>
<td>-1.810</td>
<td>-0.089</td>
<td>-0.008</td>
<td>0.057</td>
<td>1.737</td>
<td>0.184</td>
</tr>
<tr>
<td>VOLAT</td>
<td>0.016</td>
<td>0.004</td>
<td>0.010</td>
<td>0.013</td>
<td>0.019</td>
<td>0.115</td>
<td>0.011</td>
</tr>
<tr>
<td>IRECCD</td>
<td>3.255</td>
<td>1.000</td>
<td>3.000</td>
<td>3.000</td>
<td>4.000</td>
<td>5.000</td>
<td>1.079</td>
</tr>
<tr>
<td>DIFF_CONSENSUS</td>
<td>0.822</td>
<td>0.000</td>
<td>0.333</td>
<td>0.720</td>
<td>1.185</td>
<td>3.214</td>
<td>0.599</td>
</tr>
<tr>
<td>SD_REC</td>
<td>0.957</td>
<td>0.000</td>
<td>0.831</td>
<td>0.964</td>
<td>1.084</td>
<td>1.643</td>
<td>0.186</td>
</tr>
<tr>
<td>LOWEST_RATING</td>
<td>5.70</td>
<td>2.0</td>
<td>4.0</td>
<td>6.0</td>
<td>7.0</td>
<td>18.0</td>
<td>1.65</td>
</tr>
<tr>
<td></td>
<td>(AA+/Aa1) (AA-/Aa3) (A+/A2) (A-/A3) (CCC/Caa2)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RATING_SPLIT</td>
<td>1.374</td>
<td>0.000</td>
<td>1.000</td>
<td>1.000</td>
<td>2.000</td>
<td>5.000</td>
<td>0.97</td>
</tr>
<tr>
<td>NUM_RATINGS</td>
<td>2.753</td>
<td>1.000</td>
<td>3.000</td>
<td>3.000</td>
<td>3.000</td>
<td>3.000</td>
<td>0.532</td>
</tr>
</tbody>
</table>

| N                            | 3,960 |
Table 4: Summary statistics for regression variables for each period. “Pre-crisis” is the period between January 1, 2004 and June 30, 2007. “Financial crisis” is the period between July 1, 2007, and December 31, 2008. “Post-crisis” is the period between January 1, 2009 and June 30, 2012. All variables are defined in Table 1. As their name implies, balance sheet items are deflated by total assets.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Pre-crisis</th>
<th>Financial crisis</th>
<th>Post-crisis</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Median</td>
<td>Std Dev</td>
</tr>
<tr>
<td>INFLUENTIAL_RET</td>
<td>0.086</td>
<td>0.000</td>
<td>0.280</td>
</tr>
<tr>
<td>CASH.TO_ASSETS</td>
<td>0.014</td>
<td>0.008</td>
<td>0.015</td>
</tr>
<tr>
<td>DEPOSITS.TO_ASSETS</td>
<td>0.375</td>
<td>0.373</td>
<td>0.134</td>
</tr>
<tr>
<td>EQUITY.TO_ASSETS</td>
<td>0.045</td>
<td>0.044</td>
<td>0.018</td>
</tr>
<tr>
<td>ROE</td>
<td>0.161</td>
<td>0.165</td>
<td>0.090</td>
</tr>
<tr>
<td>LOG_BM</td>
<td>-0.684</td>
<td>-0.665</td>
<td>0.342</td>
</tr>
<tr>
<td>INFL_ANALYST_RET</td>
<td>0.273</td>
<td>0.000</td>
<td>0.446</td>
</tr>
<tr>
<td>INFL_ANALYST_STOCK_RET</td>
<td>0.069</td>
<td>0.000</td>
<td>0.253</td>
</tr>
<tr>
<td>FOLLOWED,FIRMS</td>
<td>0.334</td>
<td>0.175</td>
<td>0.289</td>
</tr>
<tr>
<td>PERF</td>
<td>0.017</td>
<td>0.015</td>
<td>0.072</td>
</tr>
<tr>
<td>VOLAT</td>
<td>0.010</td>
<td>0.099</td>
<td>0.003</td>
</tr>
<tr>
<td>IRECCD</td>
<td>3.365</td>
<td>3.000</td>
<td>1.051</td>
</tr>
<tr>
<td>DIFF_CONSENSUS</td>
<td>0.780</td>
<td>0.679</td>
<td>0.558</td>
</tr>
<tr>
<td>SD_REC</td>
<td>0.913</td>
<td>0.926</td>
<td>0.188</td>
</tr>
<tr>
<td>LOWEST_RATING</td>
<td>5.48</td>
<td>6.0</td>
<td>(A/A2)</td>
</tr>
<tr>
<td>RATING_SPLIT</td>
<td>1.095</td>
<td>1.000</td>
<td>0.974</td>
</tr>
<tr>
<td>NUM_RATINGS</td>
<td>2.660</td>
<td>3.000</td>
<td>0.591</td>
</tr>
<tr>
<td>N</td>
<td>1,365</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
4. Empirical Results

This section presents the results of the probit regressions testing the paper’s two hypotheses. Following Petersen (2009) and Cameron et al. (2011), I cluster standard errors in the probit regressions by firm, broker, and month in order to address biases due to cross-sectional and time series dependence, after having determined empirically that those clusters affect standard errors the most significantly.

4.1. Cash Holdings and Stockholder Uncertainty

In order to test Hypothesis 1, I include cash holdings in probit regressions of analyst influence estimated over each of the three periods in question. For purposes of comparison with the regressions presented in Section 4.2, I also include deposit levels. In unreported results, I show that this inclusion does not affect results. Table 5 presents the estimated regression parameters as well as the regression statistics and marginal effects for each period. For the sake of brevity, it does not include relative control variables and does not report the intercept, which is not statistically significant.

The first two columns of Table 5 suggest that, during quiet periods, cash holdings do not have any statistically significant effect on analyst influence. Cash holdings do not appear to be a source of uncertainty for unconcerned stockholders in the absence of stress. Deposits and profitability do not appear to influence uncertainty either. Similarly, Flannery et al. (2004) find that lending and trading assets mattered little to the market before the financial crisis. Outside of crises, stockholders appear to be uninterested in bank assets.

The probit regression also confirms a number of prior research findings associated with quiet periods. First, more equity is associated with lower analyst influence. The effect is both statistically and economically significant and consistent with the findings of Morgan (2002) and Jones et al. (2012). The marginal effect is -0.60%, which is large in comparison with the unconditional probability of 8.6%. Second, analyst influence increases with (log) B/M, with a positive
Table 5: Probit regression of analyst influence against bank cash holdings and deposit levels. The binary dependent variable (INFLUENTIAL_RET) takes the value 1 if a change in analyst recommendation influenced a bank’s stock price and 0 otherwise. Influential recommendation changes are associated with statistically significant abnormal returns after exclusion of contemporaneous disclosures, outliers, and low-price stocks, as described in Appendix A. Regression parameters are estimated over three different periods: pre-crisis (January 1, 2004 to June 30, 2007), financial crisis (July 1, 2007 to December 31, 2008), and post-crisis (January 1, 2009 to June 30, 2012). The full sample includes a total of 74 banks and 3,960 observations. Dependent variables are described in Table 1. Market controls and the intercept are not reported. ***, ** and * denote statistical significance levels of 1%, 5%, and 10%, respectively, and z statistics are reported in parentheses below parameter estimates. Marginal effects are reported to the right of coefficient estimates. The marginal effect for a continuous variable reflects the increase/decrease in predicted probability when the variable increases from the mean by one standard deviation (mean and standard deviation computed on the full sample). The marginal effect for a dummy variable reflects the increase/decrease in predicted probability when the variable changes from 0 to 1. Standard errors are clustered in three dimensions (by firm, broker, and month) to address cross-sectional and time series dependence.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Pre-crisis</th>
<th>Financial crisis</th>
<th>Post-crisis</th>
</tr>
</thead>
<tbody>
<tr>
<td>CASH/TO_ASSETS</td>
<td>3.850</td>
<td>0.71%</td>
<td>14.170*</td>
</tr>
<tr>
<td></td>
<td>(3.492)</td>
<td></td>
<td>(8.371)</td>
</tr>
<tr>
<td>DEPOSITS/TO_ASSETS</td>
<td>0.383</td>
<td>0.45%</td>
<td>0.336</td>
</tr>
<tr>
<td></td>
<td>(0.401)</td>
<td></td>
<td>(0.660)</td>
</tr>
<tr>
<td>EQUITY/TO_ASSETS</td>
<td>-3.794*</td>
<td>-0.60%</td>
<td>-2.025</td>
</tr>
<tr>
<td></td>
<td>(2.103)</td>
<td></td>
<td>(2.340)</td>
</tr>
<tr>
<td>LOG_BM</td>
<td>0.262**</td>
<td>1.58%</td>
<td>-0.051</td>
</tr>
<tr>
<td></td>
<td>(0.131)</td>
<td></td>
<td>(0.265)</td>
</tr>
<tr>
<td>LOG_SIZE</td>
<td>-0.103***</td>
<td>-0.89%</td>
<td>-0.039</td>
</tr>
<tr>
<td></td>
<td>(0.034)</td>
<td></td>
<td>(0.090)</td>
</tr>
<tr>
<td>ROE</td>
<td>0.138</td>
<td>0.14%</td>
<td>0.292</td>
</tr>
<tr>
<td></td>
<td>(0.389)</td>
<td></td>
<td>(0.652)</td>
</tr>
<tr>
<td>McFadden Pseudo $R^2$</td>
<td>0.049</td>
<td></td>
<td>0.099</td>
</tr>
<tr>
<td>Num. obs.</td>
<td>1,365</td>
<td></td>
<td>804</td>
</tr>
<tr>
<td>$\chi^2$ test</td>
<td>752.3***</td>
<td></td>
<td>394.4***</td>
</tr>
</tbody>
</table>
marginal effect of 1.58%. This effect is the opposite of that found by Loh and Stulz (2011), but lends additional support to an interpretation of the B/M ratio consistent with the findings of Huizinga and Laeven (2011). Larger discounts to book value, evidenced by a higher B/M ratio, translate stockholder valuation concerns about opaque assets and are directly associated with greater uncertainty. Third, analyst influence decreases with bank size, with a negative marginal effect of -0.89%. This is broadly consistent with prior empirical evidence, which correlates a firm’s size with the breadth of the firm’s information environment and finds that analysts are more influential when uncertainty is greater. Fourth, unreported control variables show that analysts who have been influential in the past are significantly more likely to be influential in the future (marginal effect of 5.11%) and that greater dispersion of recommendation levels dilutes analyst influence (marginal effect of -0.73%).

Columns 3 to 6 of Table 5 provide evidence of regime changes after the quiet period ending on June 30, 2007.

Most factors with explanatory power during the quiet period lose their statistical significance during the financial crisis of 2007-2009. In contrast, cash holdings are associated with significant stockholder uncertainty, with a marginal effect of 5.27% that is extremely significant compared to the unconditional probability of 9.7%. Contrary to intuition, stockholders may thus find cash holdings more a cause for concern than a source of reassurance in periods of tense liquidity. Irrespective of their source, cash holdings may raise concerns, either because they translate a weak liquidity position, or because they create heightened agency risks. Simple regressions, such as those whose results are shown in Table 5, cannot disambiguate between the two explanations. However, the next section sheds further light on this observation.

The control variables are consistent with prior literature findings. Greater dispersion of recommendations increases the likelihood that recommendation changes will be influential (marginal effect of 2.96%). Analysts recognized as experts in a stock or whose opinions diverge from the consensus exert disproportionately greater influence (marginal effects of 11.7% and 1.28%, respectively).
Likewise, brokers with broader coverage are much more likely to issue influential recommendation changes (marginal effect of 2.6%). This lends further support to the conclusion that analyst influence is more significant during crises.

After the crisis of 2007-2009, larger cash holdings are associated with lower stockholder uncertainty. The marginal effect of -1.55% is economically very significant, as it represents over a fourth of the unconditional probability of 6.0%. Larger deposit positions are also associated with lower stockholder uncertainty, with a marginal effect of -1.20%. These observations appear to lend support to the contention of Billett and Garfinkel (2004) that cash may reduce information asymmetry and bring down borrowing costs. Posting either larger cash positions or larger deposit volumes mitigates stockholder concerns. However, the setting is unusual, since the period is also characterized by deposit migration from weaker to stronger banks. Larger cash and deposit levels may thus be a sign of greater perceived bank soundness rather than a way for banks to reduce information asymmetry.

The regression results lend support to Hypothesis 1. In quiet periods, larger cash holdings do not appear to be associated with higher or lower uncertainty. Stockholders seem unconcerned or uninterested. In contrast, during periods of stress, cash holdings may be a source of either investor concern or reassurance, depending on circumstances. However, simple probit regressions make explaining these circumstances difficult.

4.2. Liquidity and Investor Uncertainty

Hypothesis 2 tests whether the higher or lower uncertainty associated with larger cash holdings is connected to liquidity issues. In order to shed further light on this subject, I interact cash holdings with deposit levels for each period. The use of deposits as a contrasting agent for revealing the nature of

13Although the use of interaction terms in logistic regression is controversial, Kolasinski and Siegel (2010) defend it as generally correct, noting that “with base probabilities not too far from zero or one, the interaction term is a good first order approximation for how
the uncertainty connected with cash holdings is motivated by their immediate demandability.

Table 6 summarizes the estimated regression parameters and the regression statistics for each period. For the sake of brevity, the table does not include relative performance and volatility and does not report the intercept.

Table 6 reveals that the interaction term is not significant before or after the crisis. Also, the interaction term neutralizes the statistical significance of the variables with explanatory power in the post-crisis probit regression.\textsuperscript{14}

Crucially, the interaction term and its two components are statistically significant during the financial crisis. Demonstrating the interaction between the three terms is not an easy matter, especially since the marginal effects of interaction terms cannot be shown in a table. Figure 1 plots a three-dimensional representation of marginal effects in a simplified probit regression model of the financial crisis excluding all variables except cash holdings, deposit levels, and the interaction term. The values taken by cash holdings and deposit levels in the figure correspond to actual values observed during the financial crisis of 2007-2009, interpolated to generate a matrix. Figure 1 shows that stockholder uncertainty is associated with a complex combination of bank cash holdings and deposit levels.

\textsuperscript{14}A VIF test suggests that this is attributable to multicollinearity between the interaction term and cash holdings. Thus, interacting cash holdings with deposits provides no additional insight in this case.

much a unit change in one covariate changes the marginal effect of another probability as a proportion of the base probability’s distance to zero or one, whichever is nearer.” This is the case with the probit regressions estimated in this paper, since base probabilities range between approximately 6\% and 10\%. Nonetheless, I confirm my results with an alternative specification of the probit regressions, in which I replace cash holdings and deposits by the ratio of cash to deposits. This ratio is statistically very significant during the financial crisis, with a p-value of 1.6 \times 10^{-5}, but not during the other two periods, which is consistent with the conclusions reached in Table 6. In addition, following the suggestion of Angrist and Pischke (2009), I estimate a linear probability regression which confirms the sign and statistical significance of the interaction term and each of the interacted variables.
Table 6: Probit regression of analyst influence against bank cash holdings interacted with deposit levels. The binary dependent variable (INFLUENTIAL RET) takes the value 1 if a change in analyst recommendation influenced a bank’s stock price and 0 otherwise. Influential recommendation changes are associated with statistically significant abnormal returns after exclusion of contemporaneous disclosures, outliers, and low-price stocks, as described in Appendix Appendix A. Regression parameters are estimated over three different periods: pre-crisis (January 1, 2004 to June 30, 2007), financial crisis (July 1, 2007 to December 31, 2008), and post-crisis (January 1, 2009 to June 30, 2012). The full sample includes a total of 74 banks and 3,960 observations. Dependent variables are described in Table 1. Broker, analyst, recommendation and market controls, and the intercept are not reported. ***, ** and * denote statistical significance levels of 1%, 5%, and 10%, respectively, and z statistics are reported in parentheses below parameter estimates. Standard errors are clustered in three dimensions (by firm, broker, and month) to address cross-sectional and time series dependence.

<table>
<thead>
<tr>
<th></th>
<th>Pre-crisis</th>
<th>Financial crisis</th>
<th>Post-crisis</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>CASH/TO/ASSETS</strong></td>
<td>3.709</td>
<td>32.352***</td>
<td>−2.393</td>
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<tr>
<td></td>
<td>(8.103)</td>
<td>(11.914)</td>
<td>(8.042)</td>
</tr>
<tr>
<td><strong>DEPOSITS/TO/ASSETS</strong></td>
<td>0.378</td>
<td>1.390*</td>
<td>−0.467</td>
</tr>
<tr>
<td></td>
<td>(0.489)</td>
<td>(0.807)</td>
<td>(0.640)</td>
</tr>
<tr>
<td><strong>CASH/TO/ASSETS*DEPOSITS/TO/ASSETS</strong></td>
<td>0.307</td>
<td>−47.076**</td>
<td>−15.160</td>
</tr>
<tr>
<td></td>
<td>(11.509)</td>
<td>(22.717)</td>
<td>(19.257)</td>
</tr>
<tr>
<td><strong>EQUITY/TO/ASSETS</strong></td>
<td>−3.788*</td>
<td>−2.050</td>
<td>0.454</td>
</tr>
<tr>
<td></td>
<td>(2.093)</td>
<td>(3.033)</td>
<td>(3.162)</td>
</tr>
<tr>
<td><strong>LOG_BM</strong></td>
<td>0.263*</td>
<td>−0.065</td>
<td>−0.140</td>
</tr>
<tr>
<td></td>
<td>(0.136)</td>
<td>(0.268)</td>
<td>(0.157)</td>
</tr>
<tr>
<td><strong>LOG_SIZE</strong></td>
<td>−0.103***</td>
<td>−0.005</td>
<td>−0.070*</td>
</tr>
<tr>
<td></td>
<td>(0.034)</td>
<td>(0.071)</td>
<td>(0.039)</td>
</tr>
<tr>
<td><strong>ROE</strong></td>
<td>0.138</td>
<td>0.457</td>
<td>0.980</td>
</tr>
<tr>
<td></td>
<td>(0.398)</td>
<td>(0.692)</td>
<td>(0.738)</td>
</tr>
<tr>
<td><strong>McFadden Pseudo R^2</strong></td>
<td>0.049</td>
<td>0.105</td>
<td>0.107</td>
</tr>
<tr>
<td><strong>Num. obs.</strong></td>
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<td>804</td>
<td>1,791</td>
</tr>
<tr>
<td><strong>χ^2 test</strong></td>
<td>752.3***</td>
<td>395.2***</td>
<td>864.1***</td>
</tr>
</tbody>
</table>
Figure 1: Marginal effects of cash holdings and deposit levels on the likelihood of analyst buy-hold-sell recommendation changes influencing bank stock prices during the financial crisis of 2007-09. The figure shows the likelihood of recommendation changes being influential (P, on the z axis) predicted by a probit regression in which cash holdings relative to assets (CASH_TO_ASSETS, x axis), deposit levels relative to assets (DEPOSITS_TO_ASSETS, y axis), and an interaction term between cash holdings and deposit levels are the dependent variables. The set of values taken by the dependent variables is derived from the actual values for a sample of 58 listed European banks during the period between July 1, 2007 and December 31, 2009 (interpolated to generate a 50x50 matrix with regularly spaced dependent variables).

First, when a bank’s cash position is limited, stockholder uncertainty increases with deposit levels. At the lowest levels of cash relative to assets observed in the sample during the financial crisis ($7.8 \times 10^{-5}$), the likelihood that recommendation changes will be influential is predicted to increase from 4.4% at the lowest observed level of deposits to assets (0.041) to 13.3% at the highest level (0.765). In contrast, analyst influence is predicted to decrease to 2.9% if
the highest observed level of deposits is combined with the highest cash holdings (0.073). This pattern suggests that stockholders fear the consequences of the demandability of deposits when a bank’s cash position is limited, lending support to the theories of Calomiris and Kahn (1991) and Flannery (1994). Stockholders monitor a bank’s liquidity position and, in particular, how deposit levels compare with cash holdings. They perceive a bank as more opaque when they are unsure how the bank will meet deposit demands. The pattern thus supports the contention of Billett and Garfinkel (2004) that cash reduces information asymmetry and may decrease borrowing costs.

Second, when deposit funding is limited, stockholder uncertainty grows as cash increases. At the lowest observed deposit levels (0.041), analyst influence is predicted to rise from 4.4% at the lowest observed cash levels ($7.8 \times 10^{-5}$) to 64.2% at the highest observed levels (0.073). While perhaps puzzling at first glance, this effect may be related to the agency risks presented by large cash positions. Large cash positions may make stockholders anxious, especially if there are few demandable deposits to discipline managers, who might, for example, be driven to acquire fire sale assets when other banks get into trouble (Acharya et al., 2011). Such moves may unnerve investors, since the acquired assets are opaque and the times, uncertain. The presence of large cash holdings may also reflect a precautionary stance adopted by management in the presence of heightened default risk, possibly because of risky assets, acute liquidity tension, or a combination of the two. In the US, the banks hoarding cash during the financial crisis were the ones with the greatest exposure to liquidity risk, owing to their illiquid asset holdings (typically mortgage-backed securities and asset-backed securities) (Cornett et al., 2011). These banks typically reacted by increasing their liquidity position and reducing lending. In contrast, banks with strong deposit funding were less affected by the crisis, and continued lending throughout the crisis. Accordingly, stockholders would have good reasons to consider banks with higher deposit levels to be less opaque. The second pattern also suggests that, in circumstances of stressed liquidity, the contention of Billett and Garfinkel (2004) may not hold. A potential explanation is that, in
such circumstances, information asymmetry becomes too much for investors to bear. Distrust sets in, and investors become wary of large cash holdings.

The regression results therefore lend support to Hypothesis 2. Although uncertainty created by agency risks cannot be clearly dissociated from uncertainty related to looming financial distress, liquidity appears to be a clear driver of the contribution of cash holdings to investor uncertainty. The robustness tests presented in the next section show that it is not directly attributable to increasing credit risk, thereby confirming Hypothesis 2.

5. Robustness Tests

5.1. Bank Cash Holdings and Credit Risk

In order to confirm that the observed pattern is not attributable to credit risk, I estimate additional regressions incorporating credit risk measurements. More specifically, I control for the lowest credit ratings assigned to banks by Standard & Poor’s, Moody’s or Fitch, as well as for rating splits. I also control for market-wide volatility using the VIX Index. The regressions are otherwise identical to those described in the previous section, except that cash and deposits are not interacted after the crisis.

Table 7 summarizes the estimated regression parameters and the regression statistics for each period. For the sake of conciseness, it does not show the intercept or variables controlling for analyst recommendations, broker and analyst characteristics, relative performance, or volatility.

The introduction of additional credit risk and market controls is associated with an approximately 20% increase in the value of the McFadden Pseudo $R^2$. In unreported tests, I confirm that this is primarily due to the credit risk controls, rather than the VIX Index. Table 7 shows that the effect observed previously is robust to the new controls. Interestingly, cash holdings, both on their own and interacted with deposit levels, become statistically significant before the crisis, with the same signs as during the crisis, hinting that stockholders may be equally sensitive to liquidity risk and vigilant to the balance between cash
Table 7: Probit regression of analyst influence against bank cash holdings interacted with deposit levels, controlling for bank leverage and credit risk. The binary dependent variable (INFLUENTIAL_RET) takes the value 1 if a change in analyst recommendation influenced a bank’s stock price and 0 otherwise. Influential recommendation changes are associated with statistically significant abnormal returns after exclusion of contemporaneous disclosures, outliers, and low-price stocks, as described in Appendix A. Regression parameters are estimated over three different periods: pre-crisis (January 1, 2004 to June 30, 2007), financial crisis (July 1, 2007 to December 31, 2008), and post-crisis (January 1, 2009 to June 30, 2012). The full sample includes a total of 74 banks and 3,960 observations. Dependent variables are described in Table 1. Broker, analyst, recommendation and market controls, and the intercept are not reported. ***, ** and * denote statistical significance levels of 1%, 5%, and 10%, respectively, and $z$ statistics are reported in parentheses below parameter estimates. Standard errors are clustered in three dimensions (by firm, broker, and month) to address cross-sectional and time series dependence.

<table>
<thead>
<tr>
<th></th>
<th>Pre-crisis</th>
<th>Financial crisis</th>
<th>Post-crisis</th>
</tr>
</thead>
<tbody>
<tr>
<td>CASH/TO/ASSETS</td>
<td>8.826</td>
<td>33.980***</td>
<td>-7.636**</td>
</tr>
<tr>
<td></td>
<td>(6.465)</td>
<td>(12.855)</td>
<td>(3.075)</td>
</tr>
<tr>
<td>DEPOSITS/TO/ASSETS</td>
<td>0.124</td>
<td>1.563**</td>
<td>-1.051**</td>
</tr>
<tr>
<td></td>
<td>(0.483)</td>
<td>(0.765)</td>
<td>(0.467)</td>
</tr>
<tr>
<td>CASH/TO/ASSETS*DEPOSITS/TO/ASSETS</td>
<td>-14.652****</td>
<td>-57.919**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(5.026)</td>
<td>(27.087)</td>
<td></td>
</tr>
<tr>
<td>EQUITY/TO/ASSETS</td>
<td>-4.508**</td>
<td>-2.078</td>
<td>1.232</td>
</tr>
<tr>
<td></td>
<td>(2.069)</td>
<td>(2.763)</td>
<td>(2.931)</td>
</tr>
<tr>
<td>LOG_BM</td>
<td>0.232</td>
<td>-0.310</td>
<td>-0.180</td>
</tr>
<tr>
<td></td>
<td>(0.145)</td>
<td>(0.228)</td>
<td>(0.145)</td>
</tr>
<tr>
<td>LOG_SIZE</td>
<td>-0.020</td>
<td>-0.002</td>
<td>-0.052</td>
</tr>
<tr>
<td></td>
<td>(0.043)</td>
<td>(0.062)</td>
<td>(0.049)</td>
</tr>
<tr>
<td>ROE</td>
<td>0.804**</td>
<td>0.488</td>
<td>0.680</td>
</tr>
<tr>
<td></td>
<td>(0.404)</td>
<td>(0.775)</td>
<td>(0.634)</td>
</tr>
<tr>
<td>LOWEST_RATING</td>
<td>0.165***</td>
<td>0.034</td>
<td>0.071**</td>
</tr>
<tr>
<td></td>
<td>(0.054)</td>
<td>(0.077)</td>
<td>(0.033)</td>
</tr>
<tr>
<td>VIX</td>
<td>0.040***</td>
<td>0.020***</td>
<td>0.027***</td>
</tr>
<tr>
<td></td>
<td>(0.015)</td>
<td>(0.005)</td>
<td>(0.007)</td>
</tr>
<tr>
<td>McFadden Pseudo $R^2$</td>
<td>0.064</td>
<td>0.118</td>
<td>0.125</td>
</tr>
<tr>
<td>Num. obs.</td>
<td>1,365</td>
<td>804</td>
<td>1,791</td>
</tr>
<tr>
<td>$\chi^2$ test</td>
<td>499.8***</td>
<td>252.2***</td>
<td>843.0***</td>
</tr>
</tbody>
</table>


holdings and deposits in the absence of a crisis. Likewise, they appear to be 
worried of high profitability in quiet times, in addition to high book leverage. 

Surprisingly, book leverage becomes statistically significant during the finan- 
cial crisis and takes a positive sign. It is as if stockholders became suspicious of 
better capitalized banks during the financial crisis, just as they were wary of too 
much cash. Iannotta (2006) finds a similar effect and proposes the explanation 
that more equity may have reflected lower asset quality not captured by credit 
ratings. He concludes that “bank capital might proxy for omitted sources of 
opaqueness.” This also appears to be a credible explanation in the context of 
this paper.

Furthermore, the credit risk controls cause the previously identified book- 
to-market and size effects to become statistically insignificant. Credit ratings 
appear to capture the uncertainty of assessing banks better than either mar- 
ket measurement. Analyst influence is more significant when credit ratings are 
lower (i.e., when LOWEST_RATING is higher). Arguably, uncertainty, too, is 
higher, which further evidences the link between analyst influence and uncer- 
tainty, consistent with prior empirical findings.

5.2. Analyst Influence, Rating Splits and Analyst Coverage

Finally, in order to assess the meaningfulness of analyst influence as a mea- 
surement of investor uncertainty, I test whether and how analyst influence re- 
lates to the proxy of opacity most commonly used in the academic literature: 
credit rating splits. I also investigate whether the results above can be replicated 
with this proxy.

Rating splits, that is, the differences in credit ratings attributed by different 
credit rating agencies to the same bonds or companies, were first introduced 
by Morgan (2002). Outside of the financial sector, Livingston et al. (2007) 
find that rating splits correlate with many proxies for asset opaqueness and 
conclude that “there is a causal link between asset opaqueness and split ratings.” 
Nonetheless, they also observe that rating splits may be unrelated to market 
measurements of opacity such as the adverse selection component of bid-ask
spreads. In the present paper, rating splits (RATING_SPLIT) are measured as the largest difference between the credit ratings assigned to a bank by Standard & Poor’s, Moody’s or Fitch. This approach is equivalent to that adopted in prior research since new senior unsecured bond issues are rated at the same level as their issuers.

The regressions reported in Table 8 incorporate rating splits as well as bank credit ratings and the control variables documented above. In unreported tests, I show that incorporating the explanatory variables presented in prior regressions leads to identical conclusions.

These regressions show that the greater levels of uncertainty reflected by rating splits are not associated with greater investor uncertainty outside of the financial crisis. This suggests that, in general, the information asymmetry reflected by rating splits may not coincide with stockholder concerns. Interestingly, this finding is consistent with the seemingly conflicting evidence of asset-induced opacity presented by Morgan (2002) and Iannotta (2006), as well as with the regime-dependent opacity reported by Flannery et al. (2004) and Flannery et al. (2013).15

However, the fact that the concern levels of stockholders may not coincide with those of other bank outsiders does not necessarily signify that the root causes of their concerns are not similar. In order to test whether credit rating disagreements stem from mismatches between cash and short-term liabilities, I estimate probit regressions of the likelihood that credit rating agencies disagree (RATING_SPLIT > 0) as a function of the explanatory variables retained in Section 4. I use the same sample described above, from which I remove variables and observations unnecessary in this new setting and exclude banks that are rated by a single credit rating agency. Also, I control for the number of credit ratings (NUM_RATINGS, between 1 and 3), the lowest rating (as above, LOWEST_RATING) and bank size (LOG_ASSETS), and I cluster standard er-

15 Data is unfortunately lacking to test whether analyst influence and the adverse selection component of the bid-ask spread coincide.
Table 8: Relationship between the likelihood that changes in analyst recommendations will influence stock prices (used as a measurement of investor uncertainty) and other uncertainty measurements over three periods of interest. The table reports the coefficients of probit regressions in which a binary dependent variable (INFLUENTIAL_RET) takes the value 1 if a change in analyst recommendation influenced a bank’s stock price and 0 otherwise, and independent variables are opacity measurements often reported in the literature as well as previous control variables (not reported for the sake of brevity). Influential recommendation changes are associated with statistically significant abnormal returns after exclusion of contemporaneous disclosures, outliers, and low-price stocks, as described in Appendix A. Regression parameters are estimated over three different periods of interest: pre-crisis (January 1, 2004 to June 30, 2007), financial crisis (July 1, 2007 to December 31, 2008), and post-crisis (January 1, 2009 to June 30, 2012). The full sample includes a total of 74 banks and 3,960 observations. Dependent variables are described in Table 1. ***, ** and * denote statistical significance levels of 1%, 5%, and 10%, respectively, and z statistics are reported in parentheses below parameter estimates. Standard errors are clustered in three dimensions (by firm, broker, and month) to address cross-sectional and time series dependence.

<table>
<thead>
<tr>
<th></th>
<th>Pre-crisis</th>
<th>Financial crisis</th>
<th>Post-crisis</th>
</tr>
</thead>
<tbody>
<tr>
<td>LOWEST.RATING</td>
<td>0.162***</td>
<td>−0.036**</td>
<td>0.051***</td>
</tr>
<tr>
<td></td>
<td>(0.043)</td>
<td>(0.015)</td>
<td>(0.019)</td>
</tr>
<tr>
<td>RATING_SPLIT</td>
<td>−0.043</td>
<td>0.188**</td>
<td>0.032</td>
</tr>
<tr>
<td></td>
<td>(0.049)</td>
<td>(0.082)</td>
<td>(0.060)</td>
</tr>
<tr>
<td>McFadden Pseudo $R^2$</td>
<td>0.057</td>
<td>0.088</td>
<td>0.083</td>
</tr>
<tr>
<td>Num. obs.</td>
<td>1,365</td>
<td>804</td>
<td>1,791</td>
</tr>
<tr>
<td>$\chi^2$ test</td>
<td>741.2***</td>
<td>401.8***</td>
<td>915.8***</td>
</tr>
</tbody>
</table>
rors by bank and quarter. Summary variables are virtually identical to those provided in tables 3 and 4 and therefore not reproduced here in the interest of brevity.

The patterns relating to cash and deposits observed before, during and after the financial crisis are strikingly similar to those observed using analyst influence instead of rating splits. During the first two periods, substantial cash positions significantly increase the probability of rating disagreements when not on a par with deposits. During the last period, substantial cash positions, like deposits, reduce this probability significantly. Puzzlingly, the combination of large cash holdings and deposit positions relative to assets has the opposite effect, as if it were a signal of weakness during the eurozone sovereign crisis. Across all periods, higher leverage and lower ratings generally increase the likelihood of disagreement, whereas size has mixed effects, consistent with prior research findings. Finally, the financial crisis resulted in rating disagreements being much more likely after the crisis, presumably as a consequence of new methodologies and greater conservatism on the part of credit rating agencies.

The empirical evidence above suggests that the two approaches yield almost identical results while suffering from similar limitations. First and perhaps most importantly, the conclusions to which either approach will lead will be significantly influenced by the periods during which they are applied. Second, whereas rating splits can only be established for firms that are closely monitored by at least two credit rating agencies, analyst influence can only be measured for listed firms with sustained analyst following. Thus the settings in which either approach can be applied differ, although there is some overlap as we demonstrate in the present paper.

6. Conclusion

In spite of inconclusive empirical evidence, the bank literature has often presumed that cash holdings reduce investor uncertainty because cash is significantly more predictable than other banking assets. This assumption ignores
Table 9: Probit regression of the likelihood of split ratings against bank cash holdings interacted with deposits. The table reports the coefficients of probit regressions in which a binary dependent variable takes the value 1 if credit ratings attributed to banks by Standard & Poor's, Moody's or Fitch differ and 0 otherwise. Independent variables are bank characteristics as well as reported control variables. Regression parameters are estimated over three different periods of interest: pre-crisis (January 1, 2004 to June 30, 2007), financial crisis (July 1, 2007 to December 31, 2008), and post-crisis (January 1, 2009 to June 30, 2012). The full sample includes a total of 67 banks and 1,288 observations. Dependent variables are described in Table 1. *** and ** denote statistical significance levels of 1% and 5%, respectively, and * denote statistical significance levels of 10%, respectively, and z statistics are reported in parentheses below parameter estimates. Standard errors are clustered in two dimensions (by firm and by quarter) to address cross-sectional and time series dependence.

<table>
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<th>Independent Variable</th>
<th>Pre-crisis</th>
<th>Financial crisis</th>
<th>Post-crisis</th>
</tr>
</thead>
<tbody>
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<td>CASH_TO_ASSETS</td>
<td>85.733***</td>
<td>362.965*</td>
<td>−15.752*</td>
</tr>
<tr>
<td></td>
<td>(26.822)</td>
<td>(197.781)</td>
<td>(8.906)</td>
</tr>
<tr>
<td>DEPOSITS_TO_ASSETS</td>
<td>3.798**</td>
<td>2.007</td>
<td>−1.796*</td>
</tr>
<tr>
<td></td>
<td>(1.742)</td>
<td>(3.679)</td>
<td>(1.038)</td>
</tr>
<tr>
<td>CASH_TO_ASSETS*DEPOSITS_TO_ASSETS</td>
<td>−156.936***</td>
<td>−467.555</td>
<td>50.989*</td>
</tr>
<tr>
<td></td>
<td>(45.744)</td>
<td>(342.589)</td>
<td>(26.293)</td>
</tr>
<tr>
<td>EQUITY_TO_ASSETS</td>
<td>−9.458</td>
<td>−11.455*</td>
<td>−16.436**</td>
</tr>
<tr>
<td></td>
<td>(8.531)</td>
<td>(5.971)</td>
<td>(7.772)</td>
</tr>
<tr>
<td>LOG_ASSETS</td>
<td>0.228*</td>
<td>0.736</td>
<td>−0.229*</td>
</tr>
<tr>
<td></td>
<td>(0.121)</td>
<td>(0.496)</td>
<td>(0.134)</td>
</tr>
<tr>
<td>LOWEST_RATING</td>
<td>0.313**</td>
<td>0.365</td>
<td>0.198*</td>
</tr>
<tr>
<td></td>
<td>(0.143)</td>
<td>(0.551)</td>
<td>(0.117)</td>
</tr>
<tr>
<td>NUM_RATINGS</td>
<td>0.085</td>
<td>1.301*</td>
<td>1.375***</td>
</tr>
<tr>
<td></td>
<td>(0.359)</td>
<td>(0.674)</td>
<td>(0.373)</td>
</tr>
<tr>
<td>McFadden Pseudo $R^2$</td>
<td>0.120</td>
<td>0.440</td>
<td>0.178</td>
</tr>
<tr>
<td>Num. obs.</td>
<td>483</td>
<td>252</td>
<td>553</td>
</tr>
<tr>
<td>$\chi^2$ test</td>
<td>167.7***</td>
<td>42.4***</td>
<td>252.2***</td>
</tr>
</tbody>
</table>
not only the agency costs of free cash flows, which have been found to increase with information asymmetry in non-regulated industries, but also the worrisome signals that large cash positions may send to investors. First, the agency costs of free cash flows may be magnified by the greater opacity of the banking industry. Behind the veil of complex disclosures, bankers may make risky asset bets unanticipated by even the most discerning investors. For this reason, large cash holdings may unnerve investors. Second, cash levels may provide direct evidence of a bank’s liquidity position and therefore of its immediate health. Large cash positions may be equally likely to reflect a bank’s precautionary stance as its potential for increased risk-taking. In situations of liquidity stress, investors may be made uneasy by cash positions exceeding the liquidity buffers warranted to meet liability holder demands. In fact, during the financial crisis, such positions have been shown to be associated with the presence of illiquid, opaque assets and the materialization of liquidity risk.

The present paper assesses whether, and under what circumstances, cash holdings contribute to stockholder uncertainty. In order to do so, I adopt a novel approach that relies on the fact that the influence of sell-side security analysts increases with uncertainty levels. More specifically, I build on the empirical framework developed by Loh and Stulz (2011) to trace stockholder uncertainty to bank cash holdings. The paper’s setting is the European banking industry during one quiet and two stressed periods (the financial crisis of 2007-2009 and ensuing period) corresponding to different macroeconomic and liquidity regimes.

I conclude that larger cash holdings relative to assets are not always associated with lower stockholder uncertainty and that the contribution of cash holdings to stockholder uncertainty is primarily driven by liquidity concerns. During periods of stress, larger cash holdings relative to assets can contribute both ways to stockholder uncertainty, depending on liquidity circumstances. More specifically, when liquidity stress reaches acute levels, larger cash levels unnerve stockholders even more when deposit levels are low relative to assets. In such circumstances, stockholders may be frightened by the agency risks that such free cash flows create – greater risk-taking leading to lower stability, as
posited by Wagner (2007b). Alternatively, stockholders may consider excessive liquidity buffers a sign of impending and potentially life-threatening liquidity problems. In circumstances of liquidity stress, stockholders also find the opposite situation — low cash levels, high deposit levels, and greater opacity — as the demandability of deposits exposes banks to heightened liquidity risks. In such situations, increasing cash levels have the effect posited by Billett and Garfinkel (2004) of reducing information asymmetry. When macroeconomic stress shifts from bank liquidity to sovereign and bank solvency, as in Europe in early 2009, both larger cash holdings and higher deposit levels reassure stockholders, an observation which appears to be consistent with the contention of Billett and Garfinkel (2004). Nonetheless, the period is further characterized by significant deposit migration from seemingly weaker to seemingly stronger banks. Larger cash and deposit levels may thus be a sign of greater perceived bank soundness rather than bank actions to reduce information asymmetry. Finally, during quiet periods, stockholders appear at first glance to be as uninterested in bank cash holdings as they are in other banking assets (Flannery et al., 2004). However, controlling for credit risk, I find a pattern similar to the one observed during the financial crisis. In fact, bank stockholders appear to monitor a bank’s cash position closely, particularly in relation to short-term liabilities. Cash holdings appearing excessive or insufficient in relation to potential short-term demands contribute to the opacity of banking institutions.

The contribution of the present paper is twofold.

First and foremost, it demonstrates the relevance of liquidity to investors and sheds light on the nature of their liquidity concerns. In doing so, it both reconciles and nuances empirical evidence as well as theoretical developments that may have appeared contradictory, including the inconclusive findings on the contribution of cash holdings to bank opacity (Morgan, 2002; Iannotta, 2006), the conclusion that the market may not be concerned about bank assets outside of a crisis period (Flannery et al., 2004, 2013), and the contention that larger cash positions may reduce information asymmetry (Billett and Garfinkel, 2004). The paper also provides additional empirical support to theories that investors
monitor bank risk-taking (e.g. Calomiris and Kahn (1991), Flannery (1994)). Importantly, it also suggests that bank liquidity may be as opaque to investors as loans and trading assets. Because of limited disclosure, investors may indiscriminately consider large liquidity buffers a reason for concern rather than a source of comfort. Cash requirements, such as those proposed by Calomiris et al. (2012), may help alleviate investor concerns, but they may not help investors fully understand bank liquidity positions. Greater transparency appears necessary for investors to better appreciate bank liquidity risks.

Second, the paper demonstrates that the empirical framework developed by Loh and Stulz (2011) can be extended to trace sources of investor uncertainty, in a similar way to credit rating splits. This approach may provide a novel lens for exploring a range of issues well beyond the banking industry or rated firms. Nonetheless, the methodology has a number of limitations. First, it can only be applied to listed companies with sustained analyst following. This may be overly restrictive in certain settings. Second, this approach only yields a binary signal of the sources of investor uncertainty. This, together with limited data granularity, may make it difficult to gain a clear understanding of certain issues. Third, the sample to which the methodology is applied may comprise multiple uncertainty regimes. Like others, the methodology may yield different conclusions depending on the choice of sample starting and cut-off dates. Synchronizing sample periods with homogeneous, well-identified macroeconomic regimes may help address this issue.
Appendix A. Technical Appendix

Recommendation Changes. Unless highlighted, the empirical approach adopted in this paper is essentially identical to that proposed by Loh and Stulz (2011). The paper assesses whether recommendation changes, rather than absolute recommendation levels, influence stock prices. Processing analyst recommendations into recommendation changes is a five-step process.

First, I reverse the I/B/E/S recommendation scale 16 so that the highest score (5) corresponds to “strong buy” and the lowest (1), to “strong sell”. Mechanically, the recommendation scale of 1 to 5 translates to a recommendation change scale of -4 to 4. Because of the structure of the I/B/E/S Historical Detail File, “zero change” recommendation changes are underrepresented.

Second, following Ljungqvist et al. (2009), I calculate recommendation changes as the difference between a broker’s new recommendation and previous recommendation, noting that changes in analyst coverage are associated with a stop signal. I consider that recommendations, unless reaffirmed or renewed, lapse after 365 days and that recommendations flagged by I/B/E/S to be “stopped” lapse on their stop date. Having observed that some stop signals are issued just before the same analysts issue new recommendations, I ignore stop signals if they are followed by a new recommendation by the same analyst in the next seven calendar days. The first recommendations issued by brokers in the sample (whether initiations or not) are mechanically considered as uninformative, except to the consensus recommendation level. Only recommendation changes are considered relevant.

Table A.1 provides the transition matrix for the processed sample of 10,111 recommendation changes obtained after this step.

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16 Analyst recommendations entered in the Thomson-Reuters I/B/E/S system are mapped to a scale of 1 (“strong buy”) to 5 (“strong sell”), regardless of the granularity of the scale used by the brokers. The wording of the underlying justification helps determine the strength of the signal. I/B/E/S also takes steps to ensure that brokers do not map recommendations to a three-notch scale.
Table A.1: Transition matrix between recommendation levels in a sample of 10,111 changes in analyst recommendations relating to listed European Banks from January 1, 2004 to June 30, 2012. The most common transitions in the sample are from 3 (hold) to 4 (buy) and from 4 to 3. Transitions from 2 (sell) to 3 (hold) and from 3 to 2 are only half as frequent. In terms of relative transitions, the transition table appears almost symmetrical with respect to the diagonal passing through “no rating changes”, as in Stickel (1995).

<table>
<thead>
<tr>
<th>From \ To</th>
<th>1 (Strong Sell)</th>
<th>2 (Sell)</th>
<th>3 (Hold)</th>
<th>4 (Buy)</th>
<th>5 (Strong Buy)</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>22</td>
<td>103</td>
<td>312</td>
<td>18</td>
<td>109</td>
<td>564</td>
</tr>
<tr>
<td></td>
<td>3.9%</td>
<td>18.3%</td>
<td>55.3%</td>
<td>3.2%</td>
<td>19.3%</td>
<td>100.0%</td>
</tr>
<tr>
<td>2</td>
<td>119</td>
<td>303</td>
<td>888</td>
<td>391</td>
<td>38</td>
<td>1739</td>
</tr>
<tr>
<td></td>
<td>6.8%</td>
<td>17.4%</td>
<td>51.1%</td>
<td>22.5%</td>
<td>2.2%</td>
<td>100.0%</td>
</tr>
<tr>
<td>3</td>
<td>309</td>
<td>966</td>
<td>662</td>
<td>1471</td>
<td>527</td>
<td>3935</td>
</tr>
<tr>
<td></td>
<td>7.9%</td>
<td>24.5%</td>
<td>16.8%</td>
<td>37.4%</td>
<td>13.4%</td>
<td>100.0%</td>
</tr>
<tr>
<td>4</td>
<td>19</td>
<td>386</td>
<td>1563</td>
<td>292</td>
<td>468</td>
<td>2728</td>
</tr>
<tr>
<td></td>
<td>0.7%</td>
<td>14.1%</td>
<td>57.3%</td>
<td>10.7%</td>
<td>17.2%</td>
<td>100.0%</td>
</tr>
<tr>
<td>5</td>
<td>109</td>
<td>50</td>
<td>548</td>
<td>393</td>
<td>45</td>
<td>1145</td>
</tr>
<tr>
<td></td>
<td>9.5%</td>
<td>4.4%</td>
<td>47.9%</td>
<td>34.3%</td>
<td>3.9%</td>
<td>100.0%</td>
</tr>
<tr>
<td>Total</td>
<td>578</td>
<td>1808</td>
<td>3973</td>
<td>2565</td>
<td>1187</td>
<td>10111</td>
</tr>
</tbody>
</table>

Prior research shows that analysts tend to herd together and that their herding behavior is amplified by short-lived information and by how informed they are (Welch, 2000; Guttman, 2010). Altunkılıç and Hansen (2009) find that recommendation changes typically have no influence by assessing the instantaneous response to recommendation revisions. They argue that analysts piggyback on recent news and events and that this creates an identification issue. Therefore, third, in order to avoid contamination by firm-specific news and events, I exclude recommendation changes that fall on the same date, as well as on adjacent trading dates (and non-trading dates falling between consecutive trading dates).17

I also exclude any recommendation change falling in a three trading-day period starting with the earnings announcement date. Because earnings announcement dates reported by I/B/E/S are not always accurate, I collect addi-

17 These exclusions go beyond those implemented by Loh and Stulz (2011).
tional data from Thomson-Reuters Earnings.com, a very accurate commercial source that has not often been tapped for such purposes. Because some earnings announcement series are missing or do not go back in time to 2004, I use announcement dates from both Earnings.com and I/B/E/S, as shown in Table A.2. However, this extra filtering does not decrease the sample size, which suggests that the first filter excludes a great deal of company-specific news.


<table>
<thead>
<tr>
<th>Sources</th>
<th>Data source</th>
<th>N</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Identical</td>
<td>Both</td>
<td>2,563</td>
<td>65.1%</td>
</tr>
<tr>
<td>I/B/E/S only</td>
<td>I/B/E/S</td>
<td>45</td>
<td>1.1%</td>
</tr>
<tr>
<td>Earnings.com only</td>
<td>Earnings.com</td>
<td>11</td>
<td>0.3%</td>
</tr>
<tr>
<td>Inconsistent</td>
<td>Both</td>
<td>1,265</td>
<td>33.5%</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>3,936</td>
<td>100.0%</td>
</tr>
</tbody>
</table>

Fourth, I exclude any recommendation change not associated with an abnormal return or abnormal turnover. I also require at least three analysts to follow stocks. I eliminate recommendation changes made when the unadjusted stock price is less than 100 times the ticker size.

Fifth, I pool the extreme positive/negative recommendation revisions because of their small number. I remove residual outliers identified as the observations to which a least trimmed square regression of CAR at each recommendation change level against a constant attributes a weight of 0. This shaves 2.6% of observations from the sample.

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18 At the time of writing, the site was being phased out but could be accessed at http://staging-retail.ccbn.com/highlight.asp?client=cb.

19 1 EUR for eurozone banks, 100 p in the UK, 1 CHF in Switzerland, 1 DKK in Denmark, 1 NOK in Norway, 1 SEK in Sweden, and 1 ISK in Iceland.

20 I pool recommendation change level -4 with -3 and recommendation change level 4 with 3.
Abnormal Returns. Unlike Loh and Stulz (2011), I calculate daily abnormal returns as differences between observed log returns and expected log returns. I use a three-factor model (Fama and French, 1992), as follows:

\[ r_{it} = b_i r_{mt} + s_i SMB_t + h_i HML_t + \epsilon_{it} \]  (A.1)

where \( r_{it} \) is the observed log return on stock \( i \) at time \( t \), \( r_{mt} \) is the observed log return on a market portfolio, \( SMB_t \) is a size factor, and \( HML_t \) is a book-to-market factor.

The STOXX Europe Total Market Index (TMI) is the market portfolio used to estimate \( r_{mt} \). STOXX TMI is a broad European index encompassing approximately 95% of free float market capitalization in Western Europe. Following Faff (2004) and Cremers et al. (2013) I estimate \( SMB_t \) and \( HML_t \) as follows:

\[ SMB_t = R_{TS,t} - R_{TL,t} \]  (A.2)
\[ HML_t = R_{TV,t} - R_{TG,t} \]  (A.3)

where \( R_{TS,t} \) is the return on the STOXX Europe TMI Small Index (a subset of STOXX Europe TMI with only small caps), \( R_{TL,t} \) is the return on the STOXX Europe TMI Large Index (another subset with only large caps); \( R_{TV,t} \) is the return on the STOXX Europe TMI Value (another subset of STOXX Europe TMI with value stocks), and \( R_{TG,t} \) is the return on the STOXX Europe TMI Growth (a subset of STOXX Europe TMI with growth stocks).

Market models are calibrated over a 60 trading-day period ending six days before the observed return (trading days -69 to -6 if the observed return is on day 0). Return data must be available and non-zero on at least 25% of trading days in the estimation period. Exchange rate risks are ignored in the regressions, a practice consistent with Fama and French (2012) and others. The shortness of the estimation period further reduces the already limited impact of these risks.

It is absolutely necessary for recommendation dates to be accurate in order to measure analyst influence precisely. I therefore examine the accuracy of a sample of 351 recommendation dates reported by I/B/E/S by comparing them
with the dates of the original analyst reports in the research repositories of one of the largest global brokers. Within the sample, there are 13 recommendations (3.7%) that cannot be reconciled with analyst reports. Within the remaining 338 recommendation dates, 270 dates (80%) are accurate, and 68 (20%) differ, most often by a day.\footnote{In such cases, the recommendation dates reported by I/B/E/S tend to be a day later than the original analyst report date, possibly because the analyst report was released after market close.}

I take a number of additional precautions to address the issue of potential inaccurate timing. First, when I/B/E/S reports a recommendation after 4:30 p.m., I consider that it does not impact prices until the next day. Second, I measure recommendation impact as the Cumulative Abnormal Return (CAR) over the interval $[-1, 0]$, where 0 is the recommendation change’s announcement date as reported by I/B/E/S (ANNDATS)\footnote{If ANNDATS is not a trading day, I take the first trading day afterwards as the reference date.}, as follows:

$$\text{CAR}[-1, 0] = \sum_{t=-1}^{0} (R_{\text{stock},t} - R_{\text{exp},t})$$ (A.4)

where $R_{\text{exp},t}$ is the expected return for stock, determined consistently with equation (A.1). As a result of these actions, the interval includes the original report date in my sample in 95.6% of cases, excluding unfound reports.\footnote{92% of cases including unfound reports.}

\textit{Influential Recommendations.} Recommendation changes are considered influential when the sign of the observed CAR is the same as the sign of the recommendation change and $\text{CAR}[-1, 0] > 1.96 \times \sqrt{2} \times \hat{\sigma}_e$, where $\hat{\sigma}_e$ is the standard deviation of the residuals of regression (A.1).

Table A.3 shows that 7.44% of recommendations are influential. Also, although the difference is limited, downgrades appear to have a greater absolute median and mean price impact than upgrades, in line with the findings of Womack (1996). This is consistent with negative analyst signals having greater imp-
Table A.3: Summary statistics for changes in analyst recommendations (recommendation changes) and Cumulative Abnormal Return (CAR) associated with recommendation changes, after exclusion of outliers. Outliers are identified through a least trimmed square regression of the response on a constant, in which outliers are attributed a weight of zero. Recommendation levels range from 1 (strong sell) to 5 (strong buy). Recommendation changes are the difference between a broker’s new recommendation and prior recommendation. Recommendation changes range from -4 (downgrade from “strong buy” to “strong sell”) to 4 (upgrade from “strong sell” to “strong buy”). Extreme negative (positive) recommendation changes are pooled in recommendation change level -3 (3). N is the sample size, and % is the percentage of the sample corresponding to each recommendation change level. MEAN, MEDIAN, STDEV, SKEW, and KURT are, respectively, the mean, median, standard deviation, skewness, and kurtosis of the distribution of CAR associated with recommendation changes. KS (Kolmogorov-Smirnov) is a statistic testing the normality of the distribution of CAR associated with recommendation changes. ***, ** and * denote statistical significance levels of this test of 1%, 5%, and 10%, respectively. “% CAR” is the percentage of positive CAR in the sample. “% Influential” is the percentage of influential recommendations.

<table>
<thead>
<tr>
<th>Rec Chg Level</th>
<th>-3</th>
<th>-2</th>
<th>-1</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>All</th>
</tr>
</thead>
<tbody>
<tr>
<td>N</td>
<td>87</td>
<td>627</td>
<td>1,535</td>
<td>664</td>
<td>1,530</td>
<td>648</td>
<td>74</td>
<td>5,165</td>
</tr>
<tr>
<td>%</td>
<td>1.93%</td>
<td>13.93%</td>
<td>34.10%</td>
<td>14.75%</td>
<td>33.99%</td>
<td>14.40%</td>
<td>1.64%</td>
<td>100.00%</td>
</tr>
<tr>
<td>MEAN</td>
<td>-0.97%</td>
<td>-0.70%</td>
<td>-0.57%</td>
<td>0.11%</td>
<td>0.57%</td>
<td>0.57%</td>
<td>0.35%</td>
<td>-0.03%</td>
</tr>
<tr>
<td>MEDIAN</td>
<td>-0.44%</td>
<td>-0.60%</td>
<td>-0.53%</td>
<td>0.06%</td>
<td>0.38%</td>
<td>0.44%</td>
<td>0.45%</td>
<td>-0.04%</td>
</tr>
<tr>
<td>STDEV</td>
<td>3.27%</td>
<td>3.02%</td>
<td>2.54%</td>
<td>2.17%</td>
<td>2.61%</td>
<td>2.42%</td>
<td>2.58%</td>
<td>2.70%</td>
</tr>
<tr>
<td>SKEW</td>
<td>-0.87</td>
<td>-0.19</td>
<td>0.1</td>
<td>0.31</td>
<td>0.39</td>
<td>-0.19</td>
<td>-0.02</td>
<td></td>
</tr>
<tr>
<td>KURT</td>
<td>1.65</td>
<td>1.69</td>
<td>1.82</td>
<td>1.63</td>
<td>1.72</td>
<td>1.73</td>
<td>2.12</td>
<td>1.89</td>
</tr>
<tr>
<td>KS</td>
<td>0.143***</td>
<td>0.078***</td>
<td>0.0753***</td>
<td>0.084***</td>
<td>0.0766***</td>
<td>0.0783***</td>
<td>0.16***</td>
<td>0.0671***</td>
</tr>
<tr>
<td>% CAR +</td>
<td>37.93%</td>
<td>39.07%</td>
<td>39.22%</td>
<td>53.01%</td>
<td>58.69%</td>
<td>59.41%</td>
<td>59.46%</td>
<td>49.03%</td>
</tr>
<tr>
<td>% Influential</td>
<td>11.49%</td>
<td>7.97%</td>
<td>6.51%</td>
<td>–</td>
<td>8.24%</td>
<td>7.10%</td>
<td>4.05%</td>
<td>7.44%</td>
</tr>
</tbody>
</table>
pact because of analysts’ reluctance to bring bad news to the market. Nearly 60% (40%) of downgrades (upgrades) are associated with negative (positive) cumulative abnormal returns. The distribution of abnormal returns associated with downgrades (upgrades) is left-skewed (right-skewed) and presents some excess kurtosis. Accordingly, a Kolmogorov-Smirnov test rejects the hypothesis of normality in all cases.
References


