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Are Banks Opaque? Evidence from Insider Trading

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Abstract

We use trades by US corporate insiders to investigate bank opacity, both in absolute terms and relative to other firms. On average, bank insider sales do not earn an abnormal return and do not predict stock returns. By contrast, bank insider purchases do, even though less than other firms. Our within-banking sector and over-time analyses also fail to provide evidence of greater opacity of banks vis-à-vis other firms. These results challenge conventional wisdom and suggest that, to assess bank opacity, the type of benchmark (transparency vs. other firms) and transaction/information (purchase/positive vs. sale/negative) are crucial.

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1. Introduction

Conventional wisdom maintains there are severe information asymmetries between a bank's management and outside investors. This argument hinges on three reasons (Morgan, 2002). First, there is limited public information on loans, the typical bank asset. There is usually no market for loans, and hence no price, and banks often grant credit based on soft, non-quantifiable information on borrowers. Second, any information disclosure by banks might quickly become out of date, as some assets can be traded in liquid markets at high frequencies. Third, high leverage may lead to significant agency problems. For example, banks might tilt their portfolios towards lower-yielding opaque assets to escape market discipline (Wagner, 2007). Overall, these arguments suggest banks are intrinsically opaque types of firms. Since opacity impairs the ability of outside investors to monitor banks, market participants alone cannot ensure financial stability. This is one of the justifications for regulating banks more than firms in any other sector.

Providing empirical support to these theoretical arguments is challenging, because opacity is hard to quantify. The approach of the existing literature is to rely on measures that, in theory, should be correlated to the degree of asymmetric information between firms and outside investors. For example, Flannery, Kwan and Nimalendran (2004, 2013) use stock-level measures of liquidity and asymmetric information, while Morgan (2002) argues that differences in the credit rating assigned to the same bond by multiple agencies indicate difficulties in assessing the value of the issuer's assets. Based on their preferred measure of opacity, these papers compare banks to other firms. Even though these firms are used as a benchmark, many of the theoretical arguments supporting bank opacity also apply to them. For example, the reserves of oil firms are not publicly traded and their size, as well as the costs to extract them, are often difficult to assess for an outsider. The same arguments apply to firms with large investments in research and development (Aboody and Lev, 2001). Hence, the approach of the existing literature is a joint test of whether banks are opaque both in absolute terms and relative to other firms. Ideally, banks and other firms should be compared to a transparency benchmark.

This paper uses returns on trades by US corporate insiders to investigate the opacity of banks, both in absolute terms and relative to other firms. The 1934 Securities and Exchange Act defines insiders as corporate officers, directors, and owners of 10 percent or more of any equity class of securities. These insiders are required to publicly disclose information on their trades, including the type of transaction, size, and execution price. Using these data, as well as stock-level data, we investigate the link between insider trading and stock returns. The logic of our test is that, if assets are hard to value for outsiders, insiders should have an informational advantage, due to their position in the firm. Since insiders can extract rents from less informed (outside) investors by trading their company's stock (eg Grossman and Stiglitz, 1980; Kyle, 1985), we should observe an abnormal increase in stock returns after purchases and an abnormal reduction following sales. Under the hypothesis that bank assets are harder to value, this variation in stock returns should be more pronounced for banks than other firms.

Empirically, we employ two methodologies to investigate these hypotheses. The first aims to test whether insiders earn abnormal profits on their trades. To this end, we employ a calendar-time portfolio approach similar to Jeng, Metrick and Zeckhauser (2003)'s. This approach consists in the construction of portfolios that, in any given month, contain the stocks traded by insiders in the previous six months. These portfolios are broken-down by type of trade, namely buy or sell, and type of company, namely firm or bank. We benchmark the returns on these portfolios against a range of asset pricing models and use the estimated intercepts as the abnormal return measures. The second method aims to examine whether insider trading predicts future stock returns. We investigate this hypothesis using a panel regression approach. This approach consists in estimating the link between the intensity of insider trading in a stock and its future return, controlling for well-known determinants of stock returns. Our prediction is that, if banks are opaque, trades by bank insiders should be profitable and predict future bank stock returns. Moreover, if banks are more opaque than other firms, the profitability and predictive power of insider trading should be higher for banks than other firms.

Our results indicate that the average bank is opaque, but only with regards to information driving stock purchases. Bank insider purchases yield abnormal profits and predict future stock returns, whereas sales do not. Comparing banks to other firms, we fail to obtain higher profits on bank transactions and stronger predictive power of bank insider trading intensity. Our findings rather suggest the opposite. A portfolio long on stocks purchased by bank insiders and short on those bought by firm insiders earns a negative abnormal return, while intensively bought bank stocks exhibit a weaker association with future returns. These results remain unchanged when we isolate information-driven trades using Cohen, Malloy and Pomorski (2012)'s opportunistic/routine trade classification. Overall, not only do these results challenge the evidence that banks are more opaque than other firms, but also question whether banks are intrinsically opaque.

We also analyse the within banking sector and time variation in opacity. Our results reveal that leverage, the size of the trading and loan book, the three main theoretical determinants of bank opacity, do not increase the predictive power of bank insider trading. In fact, the intensity of trades by insider of banks with a relatively high value of these variables is either weakly or not associated with future stock returns. Our baseline results, which reveal that bank insider trading does predict stock returns on average, seem to be driven by the median banks, namely the banks for which all the balance sheet variables in our specification are set equal to the median. The intensity of trades by insiders of these banks is positively associated with future stock returns. Compared to firm trading intensity, however, this association is weaker, providing further evidence against the hypothesis of greater bank opacity.

Our results on the time variation in opacity also contrast with conventional wisdom. There is evidence of an increase in equity market measures of liquidity and asymmetric information during the 2007-09 financial crisis (eg Flannery, Kwan and Nimalendran, 2013), in line with theories suggesting that information asymmetries worsen in periods of distress (eg Gorton, 2008). By contrast, our findings on the crisis period reveal lower (the same) profits on bank insider purchases (sales), relative to both normal times and firms. Furthermore, trading intensity does not predict bank stock returns during the crisis period, but it does in normal times. We obtain qualitatively the same results in the period leading up the financial crisis of 2007-09. This evidence questions the hypothesis of an informational advantage by bank insiders and resonates with Fahlenbrach and Stulz (2011), who document the inability of bank insiders to foresee the financial crisis of 2007-09.

Our paper is not the first one trying to establish whether banks are more opaque than other firms. Morgan (2002) shows that banks are more likely to have split ratings than other firms, suggesting that they are more opaque. By contrast, Flannery, Kwan and Nimalendran (2004) find that bank stocks have similar bid-ask spreads and price impact of trades as the stocks of other firms, indicating a similar degree of opacity. A subsequent paper by the same authors (Flannery, Kwan and Nimalendran, 2013) confirms these results, but documents larger spreads and price impact measures during financial crises. Dewally and Shao (2013) reveal a positive link between the use of financial derivatives and the opacity of banks, as measured by the correlation between bank stock prices and the market index.

The contribution of this paper is to use an approach that compares abnormal returns on trades by firm and bank insiders.[2] There are two advantages of this approach. First, it is a theory-based test of opacity, which does not rely on proxies of asymmetric information. Collin-Dufrense and Vos (2015) show that proxies such as bid-ask spread and price impact of trades do not capture informed trading. This is because it is optimal for investors with an informational advantage to shift trading to periods with abundant market liquidity and a low degree of adverse selection. Second, our approach distinguishes purchases and sales and relies on a transparency benchmark. These two features allow us to provide new insights on the absolute and relative levels of bank and firm opacity, as well as the type of information that drives opacity. Our findings reveal that banks are opaque mainly with regards to positive information, but not more than other firms.

Other papers employ data on insider trading to examine whether bank insiders foresaw the 2007-09 financial crisis. Fahlenbrach and Stulz (2011) do not find evidence of managers reducing their holding of shares before or during the crisis, which is against the hypothesis that conscious excessive risk taking caused the 2007-09 crisis. Adebambo, Brockman and Yan (2015) reach a similar conclusion comparing net purchases by managers of banks and non-financial firms. In contrast, distinguishing banks based on their exposure to the housing market and using data from 2006, Cziraki (2015) finds suggestive evidence that bank managers were able to foresee the financial crisis. Differently from these studies, our paper aims to assess whether bank insiders earned higher profits during the recent financial crisis, abstracting from their predictive ability.

This paper is structured as follows. Section 2 puts forward the theoretical foundations of our empirical test. Section 3 describes the dataset, while Section 4 presents the main methodology. Sections 5-7 present the results from comparing firms to the complete cross-section of banks, while Section 8 distinguishes banks based on a set of balance sheet characteristics. Section 9 concludes.

[2] There exists a large literature investigating whether insider traders earn abnormal profits (e.g. Seyhun, 1986, 1992) but few papers investigate the across firm variation of these returns. Aboody and Lev (2001) focus on R&D expenditures, and show that insiders in R&D firms earn a higher return. Lakonishok and Lee (2001) document that trades by insiders predict stock returns, especially for small firms. By contrast, Jeng, Metrick and Zeckhauser (2003) do not find that returns on insider trading vary with firm size.

2. Theory

This section discusses the theoretical foundations of our approach to assess bank opacity. In line with conventional wisdom, we hypothesize a greater informational advantage of bank insiders. Under this hypothesis, we claim that bank insiders should earn higher profits than their peers in firms, while their trades should exhibit a stronger predictive power. To make this argument more compelling, we need to provide a definition of informational advantage, explain its relationship with returns on insider trading and document that insiders trade to exploit it.

Our definition of informational advantage is not only restricted to specific knowledge of corporate events, such as stock repurchases, seasoned equity offerings or earning announcements. There is evidence that insider trading does occur prior to these events (eg Cziraki, Lyandres and Michaely, 2015; Aggrawal and Nasser, 2014), despite risks of legal prosecution. Our definition of informational advantage is broader than this type of specific information, as it relates to the inability of outsiders to assess the value of a company. The more severe this inability, for example because a firm invests in unique and innovative projects or a bank grants credit based on soft information, the more insiders know compared to outsiders. Overall, not only does informational advantage refer to knowledge of a specific corporate event, but also to the lack of precise information that outsiders could use to value a company.

The argument that profits increase with a trader's informational advantage is well established in the market microstructure literature. The typical model in this literature features traders with private information on the value of an asset who extract rents from liquidity (or noise) traders, whose demand for the asset is exogenous (eg Grossman and Stiglitz, 1980 and Kyle, 1985). In equilibrium, the level of informed trading is a function of two different fundamentals, depending on the type of model. In models with imperfect competition such as Kyle (1985), informed traders weigh the profits from private information against the negative impact of their trades on prices. By contrast, in price-taking models such as Grossman and Stiglitz (1980), informed trading reflects risk aversion. Traders exploit their private signal but, since this is not precise, they limit their trades to contain risk exposure. What matters for our test is that both types of models predict a positive relationship between informational advantage and trading profits, as defined as the abnormal return following insider trades (Huddart and Ke, 2007).

Finally, our test hinges on the argument that insiders trade to exploit their informational advantage. Even though the reason for trading is unobservable, existing literature provides evidence consistent with this argument (eg Seyhun, 1986 and Seyhun, 1992). Using an approach focusing on insider trades rather than returns on firms traded by insiders, Jeng, Metrick and Zeckhauser (2003) document significant abnormal returns on insider purchases but not on sales. This finding suggests other reasons why insiders might sell their stocks. Among these are liquidity needs and portfolio diversification (eg Jeng, Metrick and Zeckhauser, 2003; Fidrmuc, Goergen and Renneboog, 2006). Since their income is strongly exposed to the company's risk, insiders might diversify their portfolio into other assets or choose to sell their company's stocks to face a liquidity shock. These alternative reasons for trading imply more conservative estimates of the abnormal returns, for example because stock returns might increase after a sale transaction. To mitigate this problem, we employ Cohen, Malloy and Pomorski (2012)'s approach to disentangle routine from opportunistic trades (see Section 6).

With regards to the information content of insider trades, another potential concern are the disclosure requirements contained in the Securities and Exchange Act of 1934. By this Act, insiders must report their trades, including their type and size, to the Securities and Exchange Commission which, in turn, discloses them to the market. In theory, this should eliminate the informational advantage of insiders, because any trading based on private information would become public and prices would adjust accordingly. However, this view ignores the behaviour of insiders with long-lived information. Huddart, Hughes and Levine (2001) demonstrate the incentives of these insiders to dissimulate their information by adding noise to their demand schedule, for example by both purchasing and selling an asset conditionally on good private news. As a consequence, by foregoing some immediate profits they will be able to enjoy profits even after disclosure, because their trade does not fully reveal their information. This suggests that disclosure requirements cannot prevent insider trading, only make it less profitable.

3. Data

Our main data source is the trade-level information reported by insiders to the Securities and Exchange Commission (SEC). The Securities and Exchange Act (SEA) of 1934 prohibits trades based on material private information, namely information that a rational investor would consider relevant to the choice to buy or sell a stock. To facilitate the enforcement of these regulations, the SEA requires corporate insiders, including officers with decision-making authority in the company, board of directors and owners of more than 10% of the company's stock, to report their trades to the SEC using specific forms. Our trade-level data comes from form 4 filings, which we retrieve from Thomson Reuters.

Insiders must file Form 4 within two days from each transaction resulting in a change in beneficial ownership of any class of equity securities of their company.[3] Form 4 reports the name of the insider, its role in the company, the type of security and transaction, the transaction date, price, and size, as well as the beneficial ownership of the security following the reported transactions. Insiders are required to report transactions of non-derivative and derivative securities in two different sections, together with a specific code describing the type of transaction. There are 20 types of coded transactions, including purchases, sales, grants and awards, exercise or conversion of derivative securities.

We focus on purchases and sales of corporate stocks, as most of the papers in the insider trading literature. Purchases (sales) can be defined as transactions resulting in the acquisition (disposition)

[3] Before the enactment of the Sarbanes-Oxley Act of 2002, the reporting deadline was the tenth day after the close of the calendar month in which the transaction was executed. This reduction in the trade-disclosure interval is not a concern for our methodology, since we use the reported transaction date, rather than the filing date, as a reference point. The introduction of the Sarbanes-Oxley Act might have affected the profitability and predictive power of insider trading, since it led to a more timely information disclosure. However, investigating this hypothesis is beyond the scope of this paper (see e.g. Brochet, 2010).

of stocks either privately or through the open market. Other types of transactions involving stocks, such as the exercise of options, grants and awards, appear in our dataset only indirectly. For example, stocks obtained from the exercise of options are not considered as purchases, as they should be reported under another transaction code. Furthermore, stock options granted as part of executive compensation do not appear in our dataset as purchases or sales, since we focus only on corporate stocks. The only way stock options might show up in our data is when, after their exercise, insiders choose to sell the newly obtained stocks in the open market.

We focus on purchases and sales for which the reported transaction date falls in the period from January 1990 to December 2015. Overall, our raw data consists of 648,153 purchases and 2,353,267 sale transactions in 11,924 different stocks. To distinguish banks from other firms, we follow Flannery, Kwan and Nimalendran (2004), who define a bank as any company with a SIC code in the range 6021-6025 and 6710-6712. Based on this definition, our sample includes 743 different bank stocks, which represents 6.2% of the stocks traded by insiders. Bank stocks represent roughly 9% of purchases, but just 2% of sales. This evidence is consistent with the different compensation structure of bank insiders, which typically receive less stocks and options than firm insiders (eg Houston and James, 1995; John, De Masi and Paci, 2016). As a result, firm insiders own more stocks and, in total, their sale transactions are more numerous than those by bank insiders.

We collect data on returns from CRSP, company-level information from Compustat and bank balance sheet data from the FR-Y-9C reports filed by Bank Holding Companies and the Call Reports filed by the other banks. We match the CRSP dataset with the one on insider trades using the 8-digit CUSIP codes. Moreover, we also match on historical CUSIP codes (NCUSIP), to make sure we are not excluding firms whose identifier changed during our sample period. Finally, we merge the bank balance sheets with the CRSP and insider trades datasets using the linking tables provided by the Federal Reserve Bank of New York (2014).[4] These tables link the firm identifier in the Call Reports (RSSID) to one of the firm identifiers in CRSP (PERMCO).

4. Methodology

Existing literature employs a wide range of methods to investigate whether insiders have an informational advantage. Jeng, Metrick and Zeckhauser (2003) group these methods into two categories, namely intensive-trading and performance-evaluation. The former method relates the intensity of trading by insiders of a certain firm to the firm's future stock return, while the latter compares returns on insider trading to an expected return benchmark. The next sections explain these two methodologies and describe their advantages and disadvantages.

4.1 Performance-Evaluation Method

Performance-evaluation methods aim to test whether insiders earn abnormal profits on their trades by using a calendar-time portfolio approach. We follow the methodology of Jeng, Metrick and Zeckhauser (2003), who construct two portfolios, namely buy and sell, including all the stocks

[4] https://www.newyorkfed.org/research/banking_research/datasets.html

purchased and sold by insiders. These stocks are kept for six months and, subsequently, the portfolio is rebalanced using new trades. Hence, at each point in time, the buy (sell) portfolio includes all the stocks purchased (sold) by insiders in the previous six months.[5] The authors calculate the monthly value-weighted returns on these portfolios and regress them on a number of factors predicting stock returns. If markets are efficient, the intercept of this regression should be zero, because arbitrageurs would compete away any return in excess of risk. By contrast, this null hypothesis needs not to be accepted if insiders trade based on private information. Hence, the hypothesis of abnormal returns on insider trades can be assessed using a standard t-test on the intercept of a regression of portfolio returns on risk factors.

Since we are interested in comparing banks and firms, our approach is to break-down purchases and sales along another dimension, namely whether the trader is a firm or bank insider. This approach yields four portfolios: Buy-bank, buy-firm, sell-bank and sell-firm. For example, the buy-bank portfolio includes, at any point in time, all the stock purchases by bank insiders in the previous six months. To compare bank and firms, we construct two additional portfolios, which are long on bank transactions (purchases and sales) and short on firm transactions. We weigh all portfolios by the dollar value of the transaction.

As in Jeng, Metrick and Zeckhauser (2003), we restrict the sample to trades executed by officers and directors. Moreover, we eliminate transactions where the number of shares traded exceeds the trading volume on that day, as well as those where the price is outside the stock price range as reported in CRSP. These restrictions eliminate 23% of the trades in the original sample, which consists of all purchase and sell transactions by all insiders from January 1990 to December 2015. We note that roughly 3.6% of the trades are in bank stocks, both in the restricted sample and the excluded transactions.

Table 1 provides summary statistics for our four portfolios. In line with the descriptive statistics in Section 3, the firm portfolios contain more stocks and transactions than the bank portfolios. Moreover, the value of transactions in the firm portfolios tend to be larger, both in terms of dollar value and percentage of total market capitalization. Comparing banks and firms based on the transaction type, Table 1 reveals that the number of stocks and transactions in the sell-firm portfolio is greater than the buy-firm portfolio, whereas the opposite holds for banks. This evidence is in line with the descriptive statistics in Section 3. Finally, for both banks and firms, equally weighted and value-weighted returns, net of the risk-free rate, are larger after purchases than after sales.

To gauge the magnitude of the abnormal returns on insider trading, we estimate the following equation:

$$R_{i,t} - R_{f,t} = \alpha_i + \sum_{j \in M} \beta_j X_{j,t} + \varepsilon_{i,t} \quad (1)$$

[5] By rule 16b of the Securities and Exchange Act of 1934, known as “the short-swing” rule, insiders must surrender the profits on opposite trades (e.g. sale and subsequent purchase or purchase and subsequent sales) realized within six months from the initial trade. Hence, six months is the period of time after which insiders can revert their trades without violating the Securities and Exchange Act of 1934.

The dependent variable is the return on portfolio i in month t ($R_{i,t}$), net of the risk-free rate in month t ($R_{f,t}$). The set M consists of variables that are supposed to capture the variation in stock returns in an efficient market. Since there is no consensus on which variables to include in set M, we benchmark the returns on insider trading against a range of expected return models. We start with the most popular models in the empirical asset pricing literature, namely Fama and French (1993)'s three-factor model, Carhart (1997)'s four-factor model and Fama and French (2014)'s five-factor model. Fama and French (1993)'s factors include the value-weighted market return net of the risk-free rate in month t, $MKTRF_t$, a size and a value factor. The size factor, SMB_t, is the month t return of going long on a portfolio of small firms and short on a portfolio of large firms. The value factor, HML_t, is the month t return of going long on a portfolio of value firms (low book to market ratio) and short on a portfolio of growth firms (high book to market ratio). In addition to these factors, Carhart (1997)'s factors include momentum, MOM_t, calculated as the month t return of going long on a portfolio of high prior return stocks and short on a portfolio of low prior return stocks. Finally, Fama and French (2014)'s factors include the Fama and French (1993)'s factors, an investment and a profitability factor. The investment factor, CMA_t, is calculated as the month t return of going long on a portfolio of conservative investment firms and short on a portfolio of aggressive investment firms. The profitability factor, RMW_t, consists of the month t return of going long on a portfolio of firms with robust profitability and short on a portfolio of firms with weak profitability.[6]

In addition to the standard expected return models, we use recent models aimed to price bank stocks. Typically, financial stocks are excluded by the empirical literature on asset pricing, raising concerns on the benchmark against which our returns on bank insider trading are evaluated. To mitigate these concerns, we employ the asset pricing factors proposed by Ghandi and Lustig (2015) and Adrian, Friedman and Muir (2015). Ghandi and Lustig (2015) document an anomaly in bank stock returns, as small (large) banks earn a positive (negative) abnormal return, even after controlling for standard factors in asset pricing literature. They also show that a size factor going long on small banks and short on large banks can account for this anomaly. This factor is pro-cyclical, as it decreases during financial crises and economic downturns. Based on this evidence, Ghandi and Lustig (2015) claim that large banks are less exposed to tail risk compared to small banks, as the former enjoy implicit state guarantees.

Adrian, Friedman and Muir (2015) document that standard asset pricing models do not explain the variation of returns on financial stocks. They also show that this variation is captured by a financial capital asset pricing model (FCAPM), which includes a financial sector ROE factor (FROE) and the excess return on financials over non-financials (SPREAD) in addition to the three factors of Fama and French (1993). The FROE factor is the return on a value-weighted portfolio of financial stocks in the top 20th percentile of the ROE distribution, net of the same return on the financial stocks in the bottom 20th percentile. The FSPREAD factor is the difference between the value-weighted return on the portfolio of financials and non-financials.

[6] We download all these asset pricing factors from K. French's online data library.

Our variable of interest is the constant, α_i, which is the average return of portfolio i in excess of the compensation for the risk factors included in set M. To claim that banks are more opaque than other firms, two types of evidence are necessary. First, the α_i of the buy-bank (sell-bank) portfolio should be positive (negative). This suggests market inefficiency, because bank insiders obtain returns exceeding the compensation for risk. Second, the α_i on the long-short buy (sell) portfolio should be positive (negative), indicating a higher degree of market inefficiency for bank stocks.

4.2 Intensive-Trading Method

Intensive-trading methods aim to examine whether insider trading predicts future stock returns. These methods rely on a company-time level measure of trading intensity, which is typically based on the shares purchased and sold by insiders during a certain period, such as a month. This measure of trading intensity is then regressed on future stock returns. If insider trading is informative, intensively bought (sold) stocks should exhibit higher (lower) future returns.

To test this hypothesis, we estimate the following equation:

$$R_{i,t}^{f} = \beta_0 + \beta_1 IT_{i,t} + \beta_2 Bank_i + \beta_3 IT_{i,t} Bank_i + \beta_4 X_{i,t} + \beta_4 X_{i,t} Bank_i + \varepsilon_{i,t} \quad (2)$$

Our observations consist of stock-months for which there is insider trading activity, rather than calendar months as in the performance-evaluation approach. The dependent variable, $R_{i,t}^{f}$, is the return of a stock traded in month t calculated from month $t + 1$ to six months after the transaction. $X_{i,t}$ is a set of variables that affect stock returns, such as size, book-to-market ratio, one-month lagged returns and cumulative prior returns from twelve to two months before month t. These variables are the same as those we used as inputs for the calculation of asset pricing factors in the performance-evaluation approach. In addition, employing a panel dataset allows us to include time fixed effects as well as a range of control variables, such as market leverage and ROE. We can also add an interaction term between controls and a bank dummy, $X_{i,t}Bank_i$, to account for the different effect that the determinants of stock returns might have on banks and firms.

Our variables of interest are the insider trading indicator, $IT_{i,t}$, and its interaction with the bank dummy. In the baseline specification, we use three different insider trading indicators. The first is the Net Purchase Dummy variable, which equals one if the difference between the number of stocks bought and sold by insiders of corporation i at time t is positive. The other two indicators are continuous and capture the intensity of insider trading. One is the total net purchase by insiders of corporation i at time t, normalized by the sum of purchases and sales in the same corporation and at the same time (Net Purchase Ratio). The other measure is similar, except that the number of insiders purchasing and selling is used instead of the number of shares bought or sold (Net Buyer Ratio).

The other variable of interest is $IT_{i,t}Bank_i$. The coefficient on this interaction term indicates whether the relation between the intensity of insider trading and future stock returns is different for banks and firms. Under the hypothesis that banks are more opaque than other firms, we should expect two results. First, bank stock returns should increase in the buying intensity ($\beta_1 + \beta_3 > 0$). Second, the relationship between stock returns and buying intensity should be stronger for banks ($\beta_3 > 0$).

We estimate equation (2) on the same sample as the performance-evaluation approach. Table 1 reveals positive net purchases in 53% of the bank stock-months and 28% of the firm stock-months. By contrast, the continuous measures of insider trading, namely the Net Purchase and Buyer Ratios, are on average positive for banks and negative for firms. This evidence is consistent with the disproportionately higher fraction of firm sale transactions. Hence, even though firm insiders are on average net buyers, the average value of net purchases is negative because their sale transactions are relatively large. We also note that banks, on average, exhibit a lower book-to-market ratio and market leverage, as measured by the ratio of market capitalization and the sum of market capitalization and book value of liabilities.

4.3. Performance-Evaluation vs. Intensive-Trading Methods

Both the performance-evaluation and intensive-trading methods link stock returns and insider trading. The main difference between these two methods is the benchmark they use to assess the returns on stocks traded by insiders. Both benchmarks have advantages and disadvantages, which we illustrate in this section.

In the performance-evaluation approach, the return on the portfolios of stocks traded by insiders is compared to an expected return model. This model consists of a set of risk factors, calculated as the return on portfolios of stocks sorted by variables such as size and book-to-market ratio. These risk factors are supposed to fully explain the variation in asset prices, under the hypothesis of efficient markets. Hence, this hypothesis can be assessed through a test of statistical significance of the constant (i.e. α in equation (1)) from a regression of risk factors on asset returns. Efficient markets imply a zero constant, because any positive or negative return in excess of the compensation for risk (i.e. $\alpha>0$ or $\alpha<0$) would be arbitraged away by investors trading the asset and the benchmark portfolios. By this logic, it is possible to infer the degree of market (in-)efficiency from the estimate of α. This inference, however, relies on the correct specification of the model explaining the variation in stock returns. Since there is no consensus on the correct asset pricing model, a concern with the performance-evaluation approach is that α could be different than zero either because of market inefficiency or model misspecification. This problem is known as the "joint-hypothesis" test.

The trading-intensity approach employs a panel data regression to test the link between future stock returns and insider trading. This approach is designed to investigate hypothesis such as: "Stocks for which insiders are net buyers exhibit a higher future return than those for which insiders are net sellers". By contrast, the performance-evaluation approach examines whether the stocks traded by insiders exhibit an abnormal return, relative to a certain benchmark. Well-known variables affecting stock returns, such as size and book-to market, are included as stock-level controls in the intensive-trading approach, while in the performance-evaluation approach they are used to calculate the asset pricing factors composing the return benchmark. The correct specification of this benchmark, together with market efficiency, underpin the hypothesis of a zero α in the performance-evaluation approach. By contrast, the intensive-trading approach does not impose any restriction on regression coefficients, since it does not postulate that the set of regressors fully captures the variation in stock returns. Hence, the intensive-trading approach does not suffer from the "joint-hypothesis" problem.

Another drawback of the performance-evaluation approach is its low statistical power to detect market inefficiency (eg Loughran and Ritter, 2000). The performance-evaluation approach exploits the (calendar) time variation in the return of portfolios composed of stocks traded by insiders. These stocks are kept in the portfolio for six months after the transaction date. Hence, estimates are based on calendar month returns regardless of the amount of insider trading. For example, the return of a stock traded in June 2013 would contribute to the portfolio returns in the calendar months until December 2013, even though there might not be any other transaction in that stock after June 2013. The intensive-trading method also employs returns up to six months after the transaction date, but assigns these returns to the month when the stock was traded. The use of variation at the stock-trading month instead of calendar month level implies a higher statistical power of the intensive-trading vis-à-vis the performance evaluation method.

There are three main reasons to use the performance-evaluation approach (Jeng, Metrick and Zeckhauser, 2003). First, only with this approach is it possible to calculate stock returns from the trading date. Since the intensive-trading method exploits variation at the stock-month level, it cannot use the return in the month of the transactions used to determine the measure of trading intensity. [7] Second, the performance-evaluation approach allows us to weigh stock returns by the size of the insider trade. This is not possible with the intensive-trading approach, because this approach exploits variation at the stock-level rather than trade-level. Third, the performance-evaluation method does not require us to determine a rule to calculate the trading intensity measure, our main variable of interest.

Jeng, Metrick and Zeckhauser (2003) claim that, because of these three reasons, the performance-evaluation approach is well-suited to investigate the profits from insider trading. Calculating stock returns from the transaction date and forming purchase and sell portfolios weighted by transaction value provides an accurate measure of the returns on insider trading. By comparing these returns to a benchmark, it is possible to determine whether insiders earn abnormal profits on their trades. By contrast, the intensive-trading approach is more appropriate to investigate the predictive power of insider trading, an interesting insight for outsiders seeking returns from replicating trades by insiders.

Overall, since both the profitability and predictive power of insider trading rest on the hypothesis that insiders enjoy an informational advantage, both the performance-evaluation and intensive-trading approaches are appropriate to investigate the opacity of banks. Empirically, the former approach relies on a test of statistical significance of the αs estimated on the bank and long-bank-short-firm portfolios. These αs indicate whether bank insiders earn abnormal returns in absolute terms and relative to firms, respectively. The equivalent test in the intensive-trading approach is whether the linear combination $IT_{i,t} + IT_{i,t}BANK_i$ and the interaction term $IT_{i,t}BANK_i$ are statistically different than zero. The main difference between these two tests is that the

[7] For example, consider a stock with 1 buy and 1 sale transaction occurring on 05/05/2014 and 25/05/2014, respectively. Suppose that insiders are net buyers of that stock in May 2014. If we were to relate trading intensity in May 2014 to the return on the stock from 05/05/2014, we would be implicitly attributing a return to a transaction that did not yet occur at that time (the one on 25/05/2014). By contrast, considering the return from the date of the second transaction (25/05/2014) would neglect the period from 05/05/2104 to 25/05/2014. For this reason, most of the literature considers stock returns from the month after the transaction.

intensive-trading approach does not allow us to distinguish purchases from sales, as they are both employed to determine the trading intensity measure.

5. Baseline Results

5.1. Performance-Evaluation Method

This section presents the results obtained using the performance-evaluation method à la Jeng, Metrick and Zeckhauser (2003). Table 2 contains the OLS estimates of equation (1) using Fama and French (1993)'s three-factor model, Carhart (1997)'s four-factor model and Fama and French (2014)'s five-factor model as benchmarks. Our dependent variables are the (transaction) value-weighted monthly returns on our four portfolios, which include all the stocks bought and sold by bank and firm insiders in the previous six months.

The αs on the purchase portfolios are positive and statistically significant at the one percent level for both banks and firms, regardless of the expected return model. The abnormal return on the bank portfolio ranges between 56 and 69 basis points, while the one on the firm portfolio is larger than 100 basis points. The different magnitude of the abnormal return on bank and firm buy-portfolios is confirmed by the long-bank-short-firm portfolio, which exhibits negative and statistically significant αs, except for the three-factor model. As for the sell portfolios, Table 2 reveals a negative abnormal return for banks and, except for the five-factor models, for firms too. However, none of the αs on the sell-bank and sell-firm portfolios are statistically different than zero. Moreover, the α on the long-bank-short-firm portfolio is negative, but statistically equal to zero.

Table 3 presents the OLS estimates of equation (1) using the asset pricing factors of Ghandi and Lustig (2015) and Adrian, Friedman and Muir (2015) as a benchmark. Since these factors aim to explain variation in the stock returns of financial stocks, we only report the results for the bank and long bank-short firm portfolios. Results remain substantially unchanged. The αs on the bank-buy portfolio are positive, statistically significant, and somewhat larger than in Table 2. However, the long bank-short firm buy portfolio does not earn a positive abnormal return, suggesting that banks are not more opaque than other firms. The sell-bank and long-bank-short-firm sell portfolios still exhibit statistically insignificant αs, confirming the results in Table 2.

Overall, the results from the performance evaluation method is in line with Jeng, Metrick and Zeckhauser (2003)'s findings. Insiders earn an abnormal return on purchases but not on sales, regardless of the type of stock (financial vs. non-financial). Comparing the abnormal return on purchases by bank and firm insiders, we do not obtain that the former is greater than the latter. In fact, some specifications reveal the opposite, as the αs on the long-bank-short-firm buy portfolios are negative and statistically significant. Two insights follow from this evidence. First, banks are opaque, but not more than other firms. Second, banks are opaque only with regards to good news, which is the type of information that presumably motivates purchases. By contrast, sales are not driven by negative news or, if they are, insiders do not enjoy an informational advantage. In Section 6, we will provide a test to disentangle these two hypotheses on sales.

5.2 Intensive-Trading Method

Table 4 presents the OLS estimates of equation (2). We are interested in the coefficient on $IT_{i,t}$ and the linear combination $IT_{i,t} + IT_{i,t}BANK_i$, which capture the predictive power of trades by firm and bank insiders, respectively. The variable $IT_{i,t}$ can be any of the following indicators of insider trading activity: Net Purchase Dummy (columns 1-3), which is a dummy equal to one if insiders bought more stocks than they sold in a certain firm at a certain month, Net Purchase Ratio (columns 4-6), calculated as the total net purchase by insiders of corporation i at time t, normalized by the sum of purchases and sales in the same corporation and at the same time, and Net Buyers Ratio (columns 7-9), which is the same as Net Purchase Ratio except that the number of insiders buying or selling is used instead of the number of shares. For each dependent variable, we report three specifications: One with the standard determinants of stock returns, another augmented with return on equity and market leverage and one also including fixed effects.

In columns (1)-(3), the Net Purchase Dummy is positive and statistically significant at the one-percent level. This suggests that non-bank stocks for which insiders are net buyers exhibit a higher return than those for which insiders are net sellers. The difference in returns, which ranges between 8.8 and 9.6 percentage points, tends to be lower once we control for time fixed effects. By contrast, the interaction between the Net Purchase and the bank dummies is negative and statistically significant at the one-percent level. This indicates a smaller difference in the return of bank stocks for which insiders are net buyers and sellers. The cumulative coefficient, which is reported at the bottom of the table, reveals that net purchases by bank insiders are associated with an increase in bank stock returns ranging between 1.6 and 2.6 percentage points. Overall, trades by bank insiders predict stock returns, but to a lesser extent than those by firm insiders. These findings suggest that banks are opaque, but less so than other firms.

Results remain substantially unchanged in columns (4)-(9), where we employ continuous measures of trading intensity as indicators of insider trading. Trading intensity, as measured by the Net Purchase and Net Buyers Ratios, is associated with higher returns, but this association is weaker for bank stocks. For example, the coefficient on the Net Purchase Ratio implies that, in a scenario with only purchases in a certain firm-month ($NPR_{i,t} = 1$), the stock return is 5.5-7.6 percentage points larger than in the opposite scenario with only sales ($NPR_{i,t} = -1$). For bank stocks, the difference in the returns in those two scenarios is roughly 2 percentage points, as indicated by the linear combination of the Net Purchase Ratio and its interaction with the bank dummy. Estimates are in the same order of magnitude when we use the Net Buyers Ratio instead of the Net Purchase Ratio.

Overall, the results of the intensive-trading method are in line with those of the performance-evaluation method. The former method reveals a positive link between insider trading intensity and stock returns, controlling for standard determinants of stock returns. The performance-evaluation method suggests that returns on insider purchases outperform a range of expected return benchmarks, whereas returns on insider sales do not. Both set of results support the hypothesis that banks are opaque. Neither method, however, provides evidence indicating a greater informational advantage of bank insiders. Returns on bank insider purchases are statistically smaller or the same as those on firm insider purchases, while trades by bank insiders exhibit a lower predictive power than those by firm insiders. Hence, our evidence does not support the hypothesis that banks are more opaque than other firms, but rather suggests the opposite.

6. Routine vs. Opportunistic Trading

The interpretation of our results in Section 5 implicitly relies on the assumption of private information as the reason for trading. In fact, insiders might trade for other motives. First, an insider might sell its stocks for diversification reasons, as both its wage and stock compensation are strongly related to the performance of the company. Second, liquidity shocks can potentially induce insiders to sell their stocks. Third, discount plans on company's stocks might induce insider purchases. If these types of trading motives are more likely for banks than firms, the estimated bank-firm differences reported in Section 5 would be downward biased.

To test whether bank insiders earn a higher return than firm insiders, we would need to isolate information driven trades. To this end, we follow Cohen, Malloy and Pomorski (2012), who argue that insider trades not motivated by private information are likely to follow a specific time pattern. For example, some insiders tend to sell stocks at regular intervals to signal other motives than private information, while others buy stocks after receiving bonuses, which are usually paid in the same month of the year. Based on this logic, Cohen, Malloy and Pomorski (2012) define an insider as routine if it trades in the same month for three consecutive years. All the trades by this insider are considered as routine trades for all the subsequent years. By contrast, an opportunistic insider is an insider who traded at least once in each of the previous three years, but not necessarily in the same month[8]. As an alternative classification, Cohen, Malloy and Pomorski (2012) defines the trades occurring in the same month for at least three consecutive years as routine, while all the others as opportunistic. Hence, unlike the trader-based classification, an insider might have both opportunistic and routine trades.

In this section, we apply the performance-evaluation and intensive-trading methods by distinguishing routine from opportunistic trades. We opt for the trade-level rather than trader-level classification for two reasons. First, Cohen, Malloy and Pomorski (2012) show that their results hold regardless of the classification scheme. Second, the trade-level classification is more appropriate to the performance-evaluation method, which requires the formation of portfolios based on the type of trade as well as trader.

Using Cohen, Malloy and Pomorski (2012)'s trade-level classification, we obtain that, in the average calendar month, opportunistic trades represent the majority of trades (Table 5). The opportunistic buy (sell) portfolio contains 85% (93%) of all classified firm insider trades and 88% (92%) of all classified bank insider trades. Opportunistic purchases are larger than routine ones, both for banks and firms. Relative to market capitalization, the average value of an opportunistic

[8] For example, let us consider two insiders, A and B. Both insiders traded in June 2006, June 2008, May 2010 and December 2011 but, in 2007, insider A traded in June while B in July. Based on Cohen, Malloy and Pomorski (2012)'s algorithm, A (B) is a routine (opportunistic) insider and all its trades after 2008 are considered as routine (opportunistic) trades.

bank (firm) purchase is 71% (122%) greater than a routine one. By contrast, the average value of opportunistic sales, relative to market capitalization, is 36% larger for firms, but 2% smaller for banks.

6.1. Performance-Evaluation Method

Table 6 presents the OLS estimates of the αs in equation (1) using portfolios composed of opportunistic trades only. Results are qualitatively the same as in Table 2. Both banks and non-banks still exhibit a positive and statistically significant α on the purchase portfolio and a negative but insignificant α on the sale portfolio, regardless of the expected return model. The long bank-short firm buy portfolio yields a negative abnormal return that is statistically significant for two the three specifications, confirming that bank insiders do not enjoy a greater informational advantage. Finally, the coefficients on the asset pricing factors indicate a similar trading behaviour as in the baseline analysis.

Overall, isolating the trades that most likely contain private information, namely opportunistic trades, does not change our baseline results in Section 5. Since potential differences in trading motives do not explain why bank insiders do not earn more than firm insiders, our baseline findings suggest that bank insiders do not enjoy a greater informational advantage.

6.2. Intensive-Trading Method

Table 7 presents the OLS estimates of equation (2), using indicators of insider trading intensity only capturing opportunistic trades. As in Cohen, Malloy and Pomorski (2012), we construct Opportunistic Buy and Opportunistic Sell dummies, which are equal to one if there were any opportunistic purchases or sales, respectively, in stock i at time t. On average, 8.9% (18.9%) of the firm (bank) stock-months have at least an opportunistic purchase. By contrast, there were opportunistic sales in 32.8% (18.5%) of the firm (bank) stock-months.

Columns (1)-(3) report the coefficient on the Opportunistic Buy dummy estimated only on the sample of opportunistic trades. The coefficient is positive and statistically significant at the one-percent level. This suggests that non-bank stocks for which there is at least an opportunistic purchase exhibit a higher return than the non-bank stocks with at least an opportunistic sale. The difference in returns ranges between 7.8 and 8.8 percentage points. In line with Table 4, the interaction between the Opportunistic Buy and the bank dummy is negative and statistically significant. This indicates that the association between opportunistic purchases and stock returns is lower for banks than other firms. The cumulative effect, which we report at the bottom of the table, reveals that bank stocks with opportunistic buy transactions exhibit a 2.8-3 percentage points higher return. Overall, these findings suggest that, as in Section 5, banks are opaque, but not more than other firms.

In columns (4)-(6), we estimate equation (2) on the sample of classified opportunistic and routine trades and include the Opportunistic Sale dummy. The Opportunistic Buy dummy is still positive and statistically significant, whereas its interaction with the bank dummy is negative, although statistically significant only in one specification. The cumulative effect, however, indicates a 1.7-3 percentage points higher return on bank stocks with opportunistic purchases, relative to routine trades only. By contrast, the Opportunistic Sale dummy is negative and statistically significant at the one percent level. The coefficient on this dummy implies a 4.1-4.8 percentage points lower return on firm stocks with opportunistic sale transactions, relative to routine transactions. The interaction between the Opportunistic Sale and bank dummy is positive and statistically different than zero. This suggests that the association between opportunistic sales and stock returns is weaker for banks than non-banks. The sum of the coefficients on the bank dummy and its interaction with the Opportunistic Sale dummy, which is reported at the bottom of Table 7, is negative but not always statistically significant. Hence, bank stocks with opportunistic sale transactions do not exhibit a lower return than those with routine transactions, whereas non-bank stocks do.

Overall the intensive-trading method confirms the results from the performance-evaluation method. First, we fail to obtain a stronger predictive power of opportunistic bank insider trading. Second, we find predictive power of bank purchases but not sales. We note that these results are in line with the baseline ones. Hence, distinguishing routine from opportunistic trades suggests that the baseline results are not driven by differences in the trading motives of bank and firm insiders. For this reason, we will turn back to the baseline sample to conduct the analyses in the next sections.

7. Normal vs. Turbulent Times

Results in Sections 5 and 6 suggest that banks are not more opaque than other firms. This evidence is based on insider trades during the period from January 1990 to December 2015. In this section, we investigate whether there is time variation in bank opacity. A widespread view maintains that, after the subprime mortgage shock in August 2007, outside investors became reluctant to lend, because of their inability to assess bank solvency. This narrative is put forward as an explanation for the financial crisis of 2007-09 (eg Gorton, 2008). Based on this view, trades by bank insiders should be more profitable in crisis times, because the outsiders' inability to assess bank assets increases the informational advantage of insiders. Furthermore, another strand of literature examines whether bank insiders foresaw the financial crisis of 2007-09 using data on insider trading (eg Falenbrach and Stulz, 2012). If insiders had more precise information on the value of bank assets, not only should they have traded more right before the crisis, but their trades should have been more informative and profitable than in normal times and compared to other firms.

To test these hypotheses, we isolate trades occurring at a specific point during or before the financial crisis. We are interested in the trades from August 2007 to September 2009, which Flannery, Kwan and Nimalendran (2014) define as the crisis period, as well as those from January to July 2007, that is seven months before the financial crisis erupted (pre-crisis period). Table 8 reveals that calendar months containing trades executed during and the crisis and pre-crisis periods exhibit a higher average number of trades than in normal times. As for the size of these transactions, bank insiders sold more shares and, surprisingly, also bought more shares during the crisis. Moreover, both the crisis and pre-crisis period exhibit a higher fraction of bank stock-months with a positive Net Purchase Dummy, as well as higher Net Purchase and Net Buyers Ratios. The firm portfolio also contains more share purchases in the calendar months corresponding to the crisis period, but a higher number of shares sold in the pre-crisis period. This is also confirmed by the fraction of firm-stock months with a positive Net Purchase Dummy. As a percentage of market capitalization, however, the average transaction executed during the crisis and pre-crisis periods is smaller than normal times, for both banks and other firms. Overall, summary statistics suggest that insiders traded more intensively during the crisis and pre-crisis periods, even though the average size of their transactions, relative to market capitalization, got smaller.

7.1. Performance-Evaluation Method

In this section, we investigate the time variation in bank opacity using the performance-evaluation method. Our approach is to estimate equation (1) adding two dummies taking the value one in the calendar months August 2007-September 2009 and January-July 2007. These two dummies capture changes in abnormal returns during the crisis and pre-crisis periods, relative to the level of abnormal returns in normal times (α). Since our regression equation also includes the set of asset pricing factor discussed in Section 5, the estimated abnormal returns do not only capture market wide variation, such as the drop of stock prices during the financial crisis of 2007-09. Hence, if bank insiders foresaw the financial crisis of 2007-09 and banks became more opaque during that period, both relative to normal times and other firms, the coefficient on the pre-crisis and crisis dummies should be positive (negative) in the bank and long-bank-short-firm purchase (sell) portfolios. We should expect α to carry the same sign if banks are opaque in normal times, both in absolute terms and relative to other firms.

Table 9 contains the results. First, the estimated αs indicate positive and statistically significant abnormal returns in normal times for both banks and firms. Their magnitude is slightly larger than in Table 2 for banks, but the long-bank-short-firm buy portfolio still fails to exhibit and abnormal return. Differences appear during crisis times. In the bank-buy portfolio, the crisis dummy is negative and statistically significant in all specifications. Bank purchases earn a 2.3-2.6 percentage points lower return during the crisis period, suggesting bank insiders do not enjoy a greater informational advantage. In fact, the sign and statistical significance of the linear combination $\alpha + CRISIS$, which captures the level of abnormal return in the crisis period, indicates no informational advantage at all of bank insiders. This contrasts with the results concerning firm portfolios, where insider purchases resulted in higher returns during crisis times, indicating increased opacity.

In the pre-crisis periods, both the bank and long-bank-short-firm buy portfolios exhibit lower abnormal returns than in normal times, but this difference is statistically the same as in the crisis period. Furthermore, the sign and statistical significance of the linear combinations $\alpha + PRE-CRISIS$ suggest that bank insider purchases earn a negative abnormal return in the pre-crisis period, both in absolute terms (bank portfolio) and relative to other firms (long-bank-short-firm portfolio).

As for insider sales, the crisis dummy is not statistically significant in the bank portfolio, suggesting no difference in the profitability of bank insider trading in crisis vis-à-vis normal times. In addition, bank insider sales do not seem to be profitable at all in times of crisis, as the linear combination $\alpha + CRISIS$ is not statistically different than zero in the bank portfolio. We obtain the same result in normal times, as revealed by statistically insignificant α in the bank portfolio. Finally, the estimates from the long-bank-short-firm portfolio reveal no difference in the profitability of bank and firm insider sales, neither in crisis nor normal times.

Our evidence on bank insider sales is slightly stronger during the pre-crisis period. Both the bank and long-bank-short-firm portfolios exhibit a negative and statistically significant pre-crisis dummy at least in one specification, even though we can never reject the hypothesis that this dummy is equal to the crisis one. More importantly, the linear combination $\alpha + PRE - CRISIS$ is negative and statistically significant, at least in the bank portfolio, whereas $\alpha + CRISIS$ is not statistically different than zero. Hence, in level terms, the abnormal return on bank insider sales is negative in the pre-crisis period, but, except for one specification, statistically the same as the one on firm insider sales ($\alpha + PRE - CRISIS$ in the long-bank-short-firm portfolio). This finding suggests an informational advantage of bank insiders in the pre-crisis period, but in absolute terms rather than compared to other firms or time periods.

Overall, these findings do not support our hypotheses on the time variation of bank opacity. Bank insiders earned lower profits on purchases in the pre-crisis and crisis periods, both relative to normal times and non-banks. In addition, the bank buy portfolio exhibits positive abnormal returns in normal times, but not during our periods of interest. As for sales, we find weak evidence consistent with a greater bank opacity in times of financial distress. The bank sell portfolio exhibits a negative abnormal return in the pre-crisis period. This abnormal return, however, is not statistically different than the one in normal times and during the crisis period. Relative to non-banks, the return on bank sales during the pre-crisis period is not consistently lower either. In the next section, we investigate whether these results still hold when using the intensive trading method.

7.2. Intensive-Trading Method

This section employs the intensive-trading method to examine the time variation in bank opacity. We postulate that trades by bank insiders should have a stronger predictive power in the crisis and pre-crisis periods, both relative to normal times and other firms. To test these hypotheses, we use the same estimating equation as in Section 5, with two differences. First, we add two dummies: One taking the value one for any stock traded by insiders during the period from August 2007 to September 2009 (crisis dummy), and another equal to one for any stock traded by insiders from January to July 2007 (pre-crisis dummy). Second, we include triple interactions between the indicators of insider trading, the bank and time dummies, as well as all the pairwise combinations of these variables.

We assess our hypotheses on the time variation in bank opacity through the following tests. First, the linear combinations $IT_{i,t} + IT_{i,t}Bank_i + IT_{i,t}Pre - Crisis_t + IT_{i,t}Bank_iPre - Crisis_t$ and $IT_{i,t} + IT_{i,t}Bank_i + IT_{i,t}Crisis_t + IT_{i,t}Bank_iCrisis_t$ should be positive and statistically significant, indicating the ability of trades by bank insiders to predict stock returns in the crisis and pre-crisis periods. Second, the linear combinations $IT_{i,t}Pre - Crisis_t + IT_{i,t}Bank_iPre - Crisis_t$ and $IT_{i,t}Crisis_t + IT_{i,t}Bank_iCrisis_t$ should be positive and statistically significant, suggesting a higher predictive power of bank insider trading intensity in the crisis and pre-crisis periods, compared to normal times. Third, the linear combinations $IT_{i,t}Bank_i + IT_{i,t}Bank_iPre - Crisis_t$ and $IT_{i,t}Bank_i + IT_{i,t}Bank_iCrisis_t$, which capture the difference between the predictive power of bank and firm insider trading in the pre-crisis and crisis periods, should be positive and statistically significant. Finally, if the predictive power of insider trading is greater for banks than firms in normal times too, the interaction $IT_{i,t}Bank_i$ and the linear combination $IT_{i,t} + IT_{i,t}Bank_i$ should be positive and statistically significant.

Table 10 reports the results using the Net Purchase Dummy in columns (1)-(3), the Net Purchase Ratio in columns (4)-(6) and the Net Buyers Ratio in columns (7)-(9). For all these three measures, the linear combinations reported at the bottom of Table 10 do not reveal any predictive power of bank insider trading neither in the pre-crisis nor crisis periods, as stocks for which insiders are net buyers and net sellers in these periods exhibit (statistically) the same return. We do find a positive and statistically significant linear combination $IT_{i,t} + IT_{i,t}Bank_i$, which is consistent with the predictive power of bank insider trading in normal times.

Compared to normal times, the predictive power of trades by bank insiders does not increase in our periods of interest, as the linear combinations $IT_{i,t}Crisis_t + IT_{i,t}Bank_iCrisis_t$ and $IT_{i,t}Pre - Crisis_t + IT_{i,t}Bank_iPre - Crisis_t$ are either negative or not statistically significant. We also fail to provide evidence of a greater predictive power of bank vis-à-vis firm insider trading. Both in normal times and during the crisis period, the association between trading intensity and future stock returns is weaker for banks than firms, as indicated by negative and statistically significant interaction term $IT_{i,t}Bank_i$ and linear combination $IT_{i,t}Bank_i + IT_{i,t}Bank_iCrisis_t$. By contrast, the statistically insignificant linear combination $IT_{i,t}Bank_i + IT_{i,t}Bank_iPre - Crisis_t$ reveals no difference between the predictive power of trades by bank and firm insiders in the pre-crisis period.

Overall, our findings are not consistent with the hypothesis that bank insiders enjoyed a greater informational advantage during and right before the financial crisis of 2007-09. The intensive-trading method does not provide evidence of a higher predictive power of bank insider trading, neither compared to normal times nor other firms. In fact, some specifications suggest the opposite. In line with these results, the performance-evaluation method reveals lower (the same) profits on bank purchases (sales) before and during the crisis, relative to both normal times and other firms. Hence, in contrast with Flannery, Kwan and Nimalendran (2013), we fail to provide evidence in support of theories postulating more severe information asymmetries in times of distress.

Our results are consistent with two explanations. First, insiders enjoyed an informational advantage before and during the crisis, but did not fully exploit it. A potential reason is the higher risk of legal prosecution, as trades executed during those periods could be perceived as more likely to be scrutinized by the Security and Exchange Commission. Another reason, in line with Collin-Dufrense and Vos (2015), is the lower incentive to trade based on private information in periods of low market liquidity, such as the financial crisis of 2007-09. Since the price impact of trades is stronger in these periods, aggressive purchase or sale transactions would reveal more information than in normal times.

Second, bank insiders did not enjoy an informational advantage during the financial crisis of 2007-09, because assessing the value of bank assets might have become harder not only for outsiders. This explanation is consistent with a recent strand of literature investigating the ability of bank insiders to foresee the financial crisis of 2007-09 (eg Falenbrach and Stulz, 2011). Most of these papers provide a negative answer, based on the evidence of no abnormal flow of insider sale transactions around the crisis period. Our results provide additional evidence in line with this strand of literature, as we document that the profitability and predictive power of bank insider trades before and during the financial crisis of 2007-09 were the same as (or lower than) normal times.

8. Bank Balance Sheet Characteristics

Results in the previous Sections do not reveal a greater opacity of banks, neither in normal nor crisis times. This evidence is based on the comparison of the average bank and firm traded by corporate insiders. In this section, we focus on the within banking sector variation, investigating the link between opacity and a set of balance sheet characteristics. To this end, we only rely on the intensive-trading method. The reason is the requirement to sort banks based on multiple balance sheet variables would complicate the performance-evaluation approach, by limiting the number of banks in each portfolio.

8.1. Methodology

Theory suggests specific balance sheet characteristics affecting the degree of information asymmetries between banks and outside investors. These characteristics are the size of the loan book, trading assets and market leverage. Since loans are not traded and often granted based on soft information, banks with a large loan portfolio should be more opaque. Opacity should also increase with trading assets, as their value depends more on high-frequency fluctuations in market prices, which mandatory information disclosure is unlikely to capture in a timely manner. Finally, leverage might lead to opacity. For example, Wagner (2007) demonstrates the incentives of highly levered banks to escape market discipline by investing in more opaque activities.

To empirically investigate the link between opacity and loans, trading assets and leverage, we estimate the following panel regression:

$$R_{i,t}^{f} = \beta_0 + \beta_{IT} IT_{i,t} + \beta_l Loans_{i,t} + \beta_{l,IT} Loans_{i,t} IT_{i,t} + \beta_{ml} Mkt.Lev_{i,t} + \beta_{ml,IT} Mkt.Lev_{i,t} IT_{i,t} + \beta_{tr} Trading_{i,t} + \beta_{tr,IT} Trading_{i,t} IT_{i,t} + \sum_{b \in B} \beta_b B_{i,t}^{b} + \sum_{b \in B} \beta_{b,IT} B_{i,t}^{b}\, IT_{i,t} + \beta_X X_{i,t} + \gamma_t + \varepsilon_{i,t} \quad (3)$$

Our dependent variable, $R_{i,t}^{f}$, is the return of stock i traded in month t and compounded from month $t+1$ to six months after the transaction. We are interested in the size of the loan book, $Loans_{i,t}$, market leverage, $Mkt.Lev_{i,t}$, and the amount of trading assets, $Trading_{i,t}$, as well as the interaction between these variables and the insider trading measure $IT_{i,t}$. We normalize the size of the loan and trading book by the market value of equity and reformulate market leverage as the sum of book value of liabilities and market value of equity divided by the market value of equity. As in equation (2), we add time fixed effects and control for a set of variables affecting stock returns, $X_{i,t}$, which includes size (natural logarithm of market capitalization), (log) book-to-market ratio, one-month lagged returns and cumulative prior returns from twelve to two months before month t.

To account for other factors potentially correlated to our variables of interest and affecting the predictive power of insider trading, we add a set of balance sheet control variables, B, as well as their interaction with the insider trading measure. The set B includes measures of funding structure, loan quality and non-traditional banking activities. Funding structure, which we capture through the ratios of deposits and liquid assets[9] to total liabilities, might influence the disciplining effect of leverage and hence bank opacity. Bank opacity potentially depends on loan quality as well, as loans are more sensitive to negative rather than positive information. To measure loan quality, we use the ratio of loan loss allowance to total loans and annualized loan growth, as Falenbrach, Prilmeier and Stulz (2012) show fast bank growth is a predictor of poor performance both in the 1998 and 2007-09 financial crises. Finally, banks might operate other non-traditional banking activities in addition to asset trading, directly affecting their opacity. We capture these activities through a diversification measure, the ratio of non-interest income to the sum of non-interest and interest income, and two measures of securitization activity. These measures are outstanding securitized assets and securitization income, which Ryan, Tucker and Zhou (2016) find to be negatively associated with stock returns after insider sales. Finally, we express all our balance sheet variables as deviations from the quarterly median of their distribution across the cross-section of all listed banks.[10]

Our null hypothesis is that the predictive power of insider trading increases with market leverage, the size of the loan and trading books, as these variables are the main theoretical determinants of bank opacity. To assess this hypothesis, we estimate equation (3) on the sample of bank traded by insiders and test whether the interaction terms $Loans_{i,t}IT_{i,t}$, $Mkt.Lev_{i,t}IT_{i,t}$ and $Trading_{i,t}IT_{i,t}$, as well as their linear combination with $IT_{i,t}$, are positive and statistically significant.

We are also interested in comparing the predictive power of trading by firm and bank insiders. To this end, we jointly estimate two equations: One for the bank sample, namely equation (3), and another for the firm sample, which is the same as equation (3) except for the bank balance sheet variables. This joint estimation allows us to test whether the linear combinations of $IT_{i,t}$ and $Loans_{i,t}IT_{i,t}$, $Mkt.Lev_{i,t}IT_{i,t}$ and $Trading_{i,t}IT_{i,t}$ are statistically different than the coefficient on $IT_{i,t}$ estimated on the firm sample.

8.2. Results

Table 11 contains the results on the within banking sector variation in opacity. We only use one measure of trading intensity, the Net Purchase Dummy, to facilitate the interpretation of the coefficients. The first three columns show the estimates from the bank sample, while columns (4)-(9) report the joint estimates on the bank and firm samples. For both the individual and joint estimation, we show the results using all stock-trading month observations, restricting the sample to the period 2001-15 and controlling for securitization activity. The reason is that detailed securitization data are only available from 2001, which raises the question whether the additional controls or the shorter sample period explains the potential differences from the full sample results.

[9] Liquid assets include non-interest bearing balances, currency, coins, interest bearing balances due from deposit institutions, held-to-maturity and available-for-sale securities.

[10] On average, during our sample period, the median bank has a market leverage of 8.3, zero trading assets and a loan book larger than the market value of equity by a factor of 5.5.

Restricting the sample to bank insider trading (columns (1)-(3)), we find a positive and statistically significant Net Purchase Dummy, irrespective of the sample period and the inclusion of securitization controls. This finding indicates the predictive power of insider transactions of stocks with a median value of all the balance sheet variables included in our specification. None of the interactions with the variables of interest are consistently significant across our three specifications, even though the one with trading assets is negative and statistically different than zero when we restrict the sample to the period after 2001 (columns (2) and (3)). Overall, these results do not support our hypotheses, as they indicate that the predictive power of bank insider trading does not increase with leverage, the size of the loan and trading book.

In addition to how the predictive power of insider trading varies with balance sheet characteristics, we test whether the intensity of trades by insiders of banks with relatively high values of these characteristics are associated to future stock returns. To this end, the bottom of Table 11 reports the linear combination of the Net Purchase Dummy and its interactions with leverage, loan book and trading book size, fixing the value of these variables at the 75th percentile of their distribution across all listed banks. Only the linear combination with trading assets is positive and statistically significant, suggesting that the intensity of trades by insider of banks with a relatively large trading book predict stock returns. By contrast, net insider purchases of stocks with a relatively high leverage and large loan book are not associated to future returns.

Columns (4)-(9) report the joint results on the bank and firm samples. We note that the point estimates on the bank sample are exactly the same as those in columns (1)-(3), whereas standard errors are different. The reason is that, in the joint estimation, the bank specification is the same as in the individual one, while the variance-covariance matrix is obtained using both bank and firm observations rather than bank only. Compared to columns (1)-(3), we obtain the same level of statistical significance of the interactions with our variables of interest, as well as their linear combination with the Net Purchase Dummy. Hence, the joint estimation also fails to reveal a link between the predictive power of insider trading and our three balance sheet characteristics of interest.

Our joint estimation also allows us to compare the predictive power of trades by bank and firm insiders. To this end, we test the null hypotheses that the Net Purchase Dummy estimated on the bank sample, as well as its linear combination with our balance sheet variables of interest, are equal to the Net Purchase Dummy estimated on the firm sample. The last four rows of Table 11 report the p-value from these tests. All of them reject the null hypothesis, except for banks at the 75th percentile of the trading book distribution once we restrict the sample to the period after 2001. Hence, trades by insiders of these banks exhibit statistically the same predictive power as trades by their peers in firms, at least in two out of three specifications. By contrast, the association between future stock returns and insider trading intensity is stronger for firms than banks at the 75th percentile of the distribution of leverage and loan book size, as well as banks with a median value of all balance sheet characteristics included in equation (3).

Our evidence of no link between the predictive power of insider trading and balance sheet characteristics, such as leverage, loan and trading book size, contrasts with theoretical predictions and the existing literature on bank opacity (eg Morgan, 2002; Flannery, Kwan and Nimalendran, 2004, 2012). One potential explanation for these contrasting results is that loans or trading assets are hard to value for outsiders, but do not necessarily drive insider trading. Insiders might enjoy an informational advantage about corporate events or overall bank performance, rather than the value of specific loans or trading assets. By contrast, these assets affect the degree of asymmetric information among outsiders, because loans or trading assets might be hard to value. Hence, specific bank balance sheet characteristics could be linked to measures of liquidity or credit rating splits, as shown by the existing literature, without affecting returns on insider trading.

9. Conclusion

This paper investigates bank opacity, both in absolute terms and relative to other firms, by comparing the returns on trades by corporate insiders. The logic of our test is that, due to the higher costs of assessing the value of bank assets for outsiders, banks insiders should enjoy a greater informational advantage than firm insiders. Two empirical predictions follow from this hypothesis. First, bank insiders should earn higher profits on their trades, that is stock returns should increase (decrease) more for banks than firms after insider purchases (sales). Second, insider trading intensity should exhibit a stronger correlation with bank future stock returns.

Our empirical evidence does not support the hypothesis that banks are more opaque than other firms. Purchases by bank insiders are both profitable and informative for future stock returns, but not more than those by firm insiders. By contrast, sales by bank insiders, on average, do not earn abnormal profits nor exhibit an association with future stock returns. Hence, not only do our results reject the hypothesis of greater bank opacity, but also question the conventional wisdom that banks are intrinsically opaque, at least with regards to the information driving sales. This is a novel result, which the previous literature overlooked by failing to distinguish the type of information and comparing banks to other firms rather than a transparency benchmark.

We also provide evidence on the within bank and over time variation in opacity. In contrast to theoretical arguments, banks with high leverage, large loan and trading books do not appear more opaque than other banks and firms. However, we do find evidence that banks with a relatively large trading book are opaque in absolute levels. In contrast to Flannery, Kwan and Nimalendran (2013), our analysis does not reveal time variation in bank opacity. The profitability and predictive power of insider trading do not increase when information asymmetries are supposed to worsen, such as the period prior and during the financial crisis of 2007-09. This finding, which is in line with Fahlenbrach and Stulz (2011), suggests that bank insiders did not have an informational advantage neither before nor during the 2007-09 turmoil.

To conclude, we highlight the policy implications of our findings. One of the arguments justifying bank regulation is that outside investors cannot effectively monitor banks, because they are unable to assess their solvency. For these reasons, banks are subject to regulations, such as capital and disclosure requirements. Of course, it is possible that it is these regulations rather than the inherent nature of different business models that make banks less opaque. Testing this possibility is not really feasible, though, because it would require data from banks not subject to regulation.

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TABLE 1: Summary Statistics

	Non-Banks			Banks		
VARIABLES	N	Mean	Std. Dev.	N	Mean	Std. Dev.
Panel A: Performance-evaluation approach						
# of stocks						
Sell	312	1,868	357.5	312	100.1	37.38
Buy	312	1,346	482.0	312	133.3	47.70
# of transactions						
Sell	312	51,609	42,706	312	1,122	626.6
Buy	312	13,312	7,518	312	1,249	542.8
# of shares (millions)						
Sell	312	1,440	746.6	312	23.45	42.63
Buy	312	431.5	366.5	312	6.439	8.684
Value of transactions ($ millions)						
Sell	312	36,329	22,426	312	793.8	1,656
Buy	312	3,894	2,495	312	116.3	177.3
Value of transactions (% of market capitalization)						
Sell	312	0.133	0.121	312	0.0396	0.0295
Buy	312	0.132	0.0715	312	0.0324	0.0411
Average excess return over six months after transaction date						
Sell	312	0.0051	0.0587	312	0.0044	0.0453
Buy	312	0.0187	0.0555	312	0.0102	0.0423
Value-weighted excess return over six months after transaction date						
Sell	312	0.0049	0.0613	312	0.0047	0.0514
Buy	312	0.0172	0.0591	312	0.0129	0.0548
Panel B: Intensive-trading approach						
Average return over six months after transaction date	264,232	0.0916	1.697	18,711	0.0773	0.272
Purchase Dummy	264,232	0.280	0.449	18,711	0.530	0.499
Net Purchase Ratio	264,232	-15.49	60.38	18,711	6.781	68.96
Net Buyers Ratio	264,232	-41.58	87.66	18,711	12.04	93.75
Market Capitalization	264,232	2,432	5,193	18,711	2,864	7,806
Book to Market Ratio	264,232	3.258	3.911	18,711	0.790	0.706
Return over the months t-12 to t-2	264,232	0.259	0.832	18,711	0.153	0.325
Return in month t-1	264,232	0.0228	0.172	18,711	0.0112	0.0925
ROE	264,232	0.00843	0.145	18,711	0.0613	0.0606
Market Leverage	264,232	0.653	0.257	18,711	0.129	0.0806

This table shows summary statistics about our four combinations of buy/sell and firm/bank portfolios (Panel A), as well as the variables we use in the intensive-trading approach (Panel B). In Panel A, observations consist of calendar months. The value of transactions as a % of market value and the returns consist of averages across all the trades within a calendar month, net of the risk-free rate. The number of transactions and stocks is, respectively, the count of insider trades and different stocks traded in a certain calendar month. Finally, the number of shares and the value of transactions in $ millions are calculated as sums over all the trades within a certain calendar month. In Panel B, observations consist of stock-months with at least a trade by an insider. In both panels, the sample includes trades from January 1990 to December 2015.

TABLE 2: Performance-Evaluation Method

	Buy						Sell					
	Bank	Firm	Bank	Firm	Bank	Firm	Bank	Firm	Bank	Firm	Bank	Firm
MKTRF	0.802***	1.012***	0.772***	0.911***	0.811***	0.906***	0.937***	1.045***	0.930***	1.058***	0.936***	0.937***
	(0.0669)	(0.0448)	(0.0722)	(0.0392)	(0.0703)	(0.0554)	(0.0672)	(0.0344)	(0.0726)	(0.0333)	(0.0659)	(0.0306)
SMB	0.146	0.567***	0.155	0.595***	0.232**	0.509***	-0.182***	0.586***	-0.180***	0.582***	-0.0932	0.526***
	(0.102)	(0.0849)	(0.0991)	(0.0602)	(0.0973)	(0.0786)	(0.0673)	(0.0384)	(0.0649)	(0.0378)	(0.0595)	(0.0459)
HML	0.824***	-0.114	0.791***	-0.225***	0.867***	0.130	0.685***	-0.600***	0.677***	-0.586***	0.758***	-0.353***
	(0.114)	(0.0836)	(0.115)	(0.0712)	(0.150)	(0.107)	(0.104)	(0.0551)	(0.107)	(0.0586)	(0.130)	(0.0517)
MOM			-0.0898	-0.299***					-0.0214	0.0399		
			(0.0703)	(0.0457)					(0.0479)	(0.0279)		
CMA					-0.230	-0.413**					-0.297**	-0.417***
					(0.167)	(0.195)					(0.127)	(0.0908)
RMW					0.211*	-0.252**					0.209**	-0.256***
					(0.111)	(0.125)					(0.0894)	(0.0619)
α	0.00612***	0.0103***	0.00690***	0.0129***	0.00567**	0.0124***	-0.00196	-0.00123	-0.00177	-0.00157	-0.00225	0.000900
	(0.00232)	(0.00171)	(0.00244)	(0.00166)	(0.00231)	(0.00201)	(0.00194)	(0.00106)	(0.00205)	(0.00110)	(0.00200)	(0.00101)
N	312	312	312	312	312	312	312	312	312	312	312	312
R-squared	0.522	0.751	0.528	0.805	0.534	0.766	0.660	0.913	0.661	0.914	0.678	0.928
α (Long-Short)	-0.00416		-0.00596**		-0.00671**		-0.000731		-0.000205		-0.00315	
	(0.00262)		(0.00276)		(0.00276)		(0.00215)		(0.00229)		(0.00219)	

This table presents the performance-evaluation results for our four portfolios: Buy-bank, buy-firm, sell-bank, and sell-firm. These portfolios include all the transactions executed over the previous six months. The table shows the point estimates and the heteroskedasticity-robust standard errors (in parenthesis) of the factors included in 3, 4 and 5 factor models, namely MKTRF, SMB, HML, MOM, CMA and RMW. These factors are returns to zero-investment portfolios capturing market, size, value, momentum, investment and profitability effects, respectively (see references in the text for details on the construction of these factors). The intercept of the regression line, α, is our variable of interest. The two bottom rows display the α, and its corresponding standard error, estimated on a portfolio long on banks and short on other firms. The symbols *, ** and *** indicate statistical significance at the 10, 5 and 1% levels.

TABLE 3: Performance-Evaluation Method (Bank Asset Pricing Factors)

	Buy			Sell		
MKTRF	0.796***	0.666***	0.664***	0.932***	0.823***	0.821***
	(0.0666)	(0.0523)	(0.0523)	(0.0670)	(0.0518)	(0.0518)
SMB	0.140	0.241***	0.237***	-0.187***	-0.0573	-0.0600
	(0.102)	(0.0849)	(0.0851)	(0.0670)	(0.0587)	(0.0587)
HML	0.821***	0.239**	0.240**	0.683***	0.172*	0.173*
	(0.113)	(0.0952)	(0.0954)	(0.103)	(0.0893)	(0.0895)
BANK SIZE	-0.00553*		-0.00295	-0.00441*		-0.00204**
	(0.00323)		(0.00183)	(0.00229)		(0.000961)
FROE		-0.120***	-0.120***		0.00989	0.00978
		(0.0331)	(0.0330)		(0.0387)	(0.0386)
SPREAD		0.538***	0.536***		0.498***	0.496***
		(0.0623)	(0.0624)		(0.0635)	(0.0636)
α	0.00601**	0.0107***	0.0106***	-0.00205	0.00119	0.00113
	(0.00232)	(0.00190)	(0.00191)	(0.00195)	(0.00167)	(0.00168)
N	312	312	312	312	312	312
R-squared	0.524	0.668	0.669	0.662	0.770	0.771
α (Long-Short)	-0.00435*	-0.000429	-0.000611	-0.000862	0.00248	0.00237
	(0.00261)	(0.00252)	(0.00253)	(0.00215)	(0.00188)	(0.00188)

This table presents the performance-evaluation results for the buy-bank and sell-bank portfolios. These portfolios include all the transactions executed over the previous six months. The table shows the point estimates and the heteroskedasticity-robust standard errors (in parenthesis) of the factors included in 3 factor models, as well as other pricing factors specific to bank stocks. These are Ghandi and Lustig (2015)'s factor (BANK SIZE) and Adrian, Friedman and Muir (2015)'s FROE and SPREAD factors. See the references in the text for details on the construction of these factors. The intercept of the regression line, α, is our variable of interest. The two bottom rows display the α, and its corresponding standard error, estimated on a portfolio long on banks and short on other firms. The symbols *, ** and *** indicate statistical significance at the 10, 5 and 1% levels.

TABLE 4: Intensive-Trading Method

	Net Purchase Dummy			Net Purchase Ratio			Net Buyers Ratio		
BANK	-0.171***	-0.265***	-0.274***	-0.275***	-0.380***	-0.360***	-0.211***	-0.303***	-0.306***
	(0.0313)	(0.0358)	(0.0348)	(0.0308)	(0.0352)	(0.0339)	(0.0308)	(0.0352)	(0.0342)
IT	0.095***	0.096***	0.0887***	0.041***	0.0411***	0.0405***	0.049***	0.0496***	0.0463***
	(0.00352)	(0.00353)	(0.00339)	(0.00201)	(0.00202)	(0.00194)	(0.00184)	(0.00184)	(0.00178)
BANKxIT	-0.079***	-0.078***	-0.062***	-0.032***	-0.031***	-0.0271***	-0.039***	-0.039***	-0.031***
	(0.00595)	(0.00591)	(0.00543)	(0.00356)	(0.00353)	(0.00332)	(0.00319)	(0.00316)	(0.00290)
MV	-0.011***	-0.015***	-0.0127***	-0.015***	-0.018***	-0.0158***	-0.011***	-0.015***	-0.013***
	(0.00105)	(0.00106)	(0.00105)	(0.00106)	(0.00106)	(0.00105)	(0.00105)	(0.00106)	(0.00105)
BM	0.025***	0.0351***	0.0394***	0.019***	0.0331***	0.0373***	0.026***	0.0350***	0.0393***
	(0.00290)	(0.00338)	(0.00325)	(0.00287)	(0.00337)	(0.00323)	(0.00290)	(0.00339)	(0.00325)
$RET_{t-12,t-2}$	-0.022***	-0.024***	-0.0158***	-0.025***	-0.028***	-0.0184***	-0.022***	-0.025***	-0.016***
	(0.00255)	(0.00257)	(0.00250)	(0.00260)	(0.00261)	(0.00253)	(0.00255)	(0.00257)	(0.00250)
RET_{t-1}	-0.054***	-0.063***	-0.0355***	-0.076***	-0.085***	-0.0523***	-0.053***	-0.062***	-0.034***
	(0.0119)	(0.0117)	(0.0120)	(0.0120)	(0.0118)	(0.0120)	(0.0119)	(0.0117)	(0.0120)
BANKxMV	0.008***	0.0120***	0.0139***	0.0112***	0.0156***	0.0164***	0.008***	0.0120***	0.0139***
	(0.00176)	(0.00209)	(0.00197)	(0.00175)	(0.00207)	(0.00194)	(0.00176)	(0.00209)	(0.00197)
BANKxBM	-0.0136*	-0.0124	-0.0422***	-0.00697	-0.00934	-0.0377***	-0.0141*	-0.0123	-0.042***
	(0.00776)	(0.00768)	(0.00711)	(0.00773)	(0.00767)	(0.00705)	(0.00775)	(0.00768)	(0.00709)
BANKx$RET_{t-12,t-2}$	0.105***	0.101***	0.116***	0.108***	0.103***	0.117***	0.106***	0.101***	0.117***
	(0.0133)	(0.0129)	(0.0131)	(0.0133)	(0.0129)	(0.0130)	(0.0133)	(0.0129)	(0.0131)
BANKxRET_{t-1}	0.0517*	0.0558**	0.117***	0.0684**	0.0719**	0.130***	0.0522*	0.0563**	0.118***
	(0.0285)	(0.0283)	(0.0273)	(0.0286)	(0.0284)	(0.0272)	(0.0284)	(0.0282)	(0.0273)
ROE		0.179***	0.172***		0.171***	0.165***		0.179***	0.171***
		(0.0179)	(0.0171)		(0.0180)	(0.0171)		(0.0179)	(0.0171)
BANKxROE		0.0567	-0.140***		0.0638	-0.139***		0.0580	-0.139***
		(0.0599)	(0.0461)		(0.0596)	(0.0458)		(0.0599)	(0.0461)
MKT. LEV		-0.0315***	-0.0279***		-0.0503***	-0.0436***		-0.029***	-0.025***
		(0.00740)	(0.00697)		(0.00744)	(0.00698)		(0.00742)	(0.00699)
BANKxMKT. LEV		-0.00438	-0.110**		0.0150	-0.0932*		-0.00704	-0.113**
		(0.0625)	(0.0526)		(0.0621)	(0.0517)		(0.0628)	(0.0531)
CONSTANT	0.271***	0.352***	0.305***	0.388***	0.481***	0.413***	0.317***	0.396***	0.346***
	(0.0213)	(0.0224)	(0.0222)	(0.0214)	(0.0225)	(0.0221)	(0.0212)	(0.0223)	(0.0220)
Observations	280,229	280,229	280,229	280,229	280,229	280,229	280,229	280,229	280,229
R-squared	0.011	0.013	0.097	0.008	0.010	0.095	0.011	0.013	0.097
IT+BANKxIT	0.0162	0.0169	0.0262	0.0097	0.0102	0.0134	0.0096	0.0101	0.0149
p-val	0.0007	0.0003	0.0000	0.0009	0.0004	0.0000	0.0002	0.0000	0.0000

This table presents the results from the intensive-trading method. Observations are stock-months with at least a trade by an insider. Our variables of interest are IT, which is either the Net Purchase Dummy (columns 1-3), Net Purchase Ratio (columns 4-6) or Net Buyers Ratio (columns 7-9), and its interaction with a bank dummy. The Net Purchase Dummy takes the value one in stock-months where the value of insider purchases is higher than insider sales. The Net Purchase Ratio equals the difference between the value of insider purchases and sales, normalized by the sum of insider purchases and sales in a stock-month. Finally, Net Buyers Ratio is defined as the Net Purchase Ratio, except that the number of insiders buying and selling is used instead of transaction values. Control variables include the log of market capitalization (MV), the log of book to market ratio (BM), cumulative stock returns over the months t-12 to t-2 ($RET_{t-12,\,t-2}$), stock return in month t-1 (RET_{t-1}), market leverage (MKT. LEV., calculated as the ratio of market value of equity and the sum of market value of equity and book value of liabilities) and return on equity (ROE). Month fixed effects are included where indicated. Standard errors are clustered at the firm level and are reported in parenthesis; 1%, 5% and 10% statistical significance is indicated with ***, ** and * respectively. The bottom of the table reports the linear combination of the insider trading indicator and its interaction with the bank dummy (IT+BANKxIT), as well as the corresponding p-value from a test of statistical significance.

TABLE 5: Routine & Opportunistic Trades (Summary Statistics)

	Non-Banks			Banks		
	N	Mean	Std. Dev.	N	Mean	Std. Dev.
Panel A: Performance-evaluation approach						
# of stocks						
Routine Sell	288	167.0	92.33	276	4.822	2.725
Opportunistic Sell	300	1,338	288.9	300	66.06	22.03
Routine Buy	288	75.41	25.33	285	11.05	5.054
Opportunistic Buy	300	800.3	294.5	300	92.39	30.58
# of transactions						
Routine Sell	288	1,964	1,764	276	47.26	104.8
Opportunistic Sell	300	26,496	23,891	300	566.1	395.8
Routine Buy	288	917.8	525.6	285	67.56	49.97
Opportunistic Buy	300	5,476	3,805	300	514.4	253.2
# of shares (millions)						
Routine Sell	288	46.05	33.19	276	0.504	1.562
Opportunistic Sell	300	586.6	301.7	300	8.030	12.88
Routine Buy	288	17.15	13.43	285	0.134	0.244
Opportunistic Buy	300	134.4	82.27	300	2.449	3.707
Value of transactions ($ millions)						
Routine Sell	288	1,239	965.1	276	14.71	31.78
Opportunistic Sell	300	16,368	10,088	300	269.0	502.8
Routine Buy	288	184.9	170.7	285	1.894	3.157
Opportunistic Buy	300	1,453	1,026	300	33.28	25.90
Value of transactions (% of market capitalization)						
Routine Sell	288	0.0687	0.0482	276	0.0310	0.0925
Opportunistic Sell	300	0.0936	0.0795	300	0.0301	0.0274
Routine Buy	288	0.0718	0.0494	285	0.0117	0.0189
Opportunistic Buy	300	0.123	0.0936	300	0.0260	0.0317
Average return over six months after transaction date						
Routine Sell	288	0.0104	0.0588	276	0.00952	0.0570
Opportunistic Sell	300	0.00924	0.0549	300	0.00706	0.0448
Routine Buy	288	0.0133	0.0664	285	0.00943	0.0437
Opportunistic Buy	300	0.0196	0.0574	300	0.0135	0.0421
Value-weighted return over six months after transaction date						
Routine Sell	288	0.00874	0.0738	276	0.0103	0.0635
Opportunistic Sell	300	0.00991	0.0558	300	0.00474	0.0621
Routine Buy	288	0.00694	0.0782	285	0.00920	0.0627
Opportunistic Buy	300	0.0172	0.0640	300	0.0152	0.0566
Panel B: Intensive-trading approach						
OP	313,222	0.0890	0.285	23,303	0.189	0.392
OS	313,222	0.328	0.469	23,303	0.185	0.388
RP	313,222	0.0164	0.127	23,303	0.0378	0.191
RS	313,222	0.0346	0.183	23,303	0.0103	0.101

This table shows summary statistics on transaction/firm portfolios (Panel A) and the variables used in the intensive-trading approach (Panel B), distinguishing routine from opportunistic trades. Opportunistic and routine trades are defined as in Cohen, Malloy and Pomorski (2012). In Panel A, observations consist of calendar months and statistics are calculated as in Table 1. In Panel B, observations consist of stock-months with at least a trade by an insider. In both panels, the sample includes trades from January 1990 to December 2015.

TABLE 6: Opportunistic Trades Only (Performance-Evaluation Method)

	Buy						Sell					
	Bank	Firm	Bank	Firm	Bank	Firm	Bank	Firm	Bank	Firm	Bank	Firm
MKTRF	0.757***	1.025***	0.744***	0.892***	0.821***	0.926***	0.917***	1.007***	0.914***	1.031***	0.913***	0.953***
	(0.0748)	(0.0556)	(0.0801)	(0.0511)	(0.0788)	(0.0690)	(0.0732)	(0.0314)	(0.0795)	(0.0318)	(0.0747)	(0.0337)
SMB	0.104	0.520***	0.108	0.564***	0.201**	0.479***	-0.222***	0.544***	-0.221***	0.536***	-0.165***	0.519***
	(0.0935)	(0.106)	(0.0912)	(0.0742)	(0.102)	(0.0960)	(0.0624)	(0.0370)	(0.0606)	(0.0346)	(0.0632)	(0.0439)
HML	0.750***	-0.0298	0.737***	-0.171*	0.669***	0.200	0.739***	-0.439***	0.736***	-0.413***	0.807***	-0.314***
	(0.109)	(0.111)	(0.112)	(0.0921)	(0.150)	(0.139)	(0.108)	(0.0423)	(0.113)	(0.0443)	(0.140)	(0.0480)
MOM			-0.0376	-0.384***					-0.00849	0.0689**		
			(0.0563)	(0.0509)					(0.0467)	(0.0267)		
CMA					0.00790	-0.404**					-0.234*	-0.215**
					(0.158)	(0.193)					(0.137)	(0.0951)
RMW					0.285**	-0.203					0.120	-0.118**
					(0.113)	(0.158)					(0.0892)	(0.0572)
α	0.00628**	0.0109***	0.00660***	0.0141***	0.00488**	0.0127***	-0.00183	-0.00109	-0.00175	-0.00167	-0.00189	-5.30e-05
	(0.00247)	(0.00218)	(0.00253)	(0.00208)	(0.00238)	(0.00245)	(0.00210)	(0.00105)	(0.00224)	(0.00107)	(0.00214)	(0.00112)
N	300	300	300	300	300	300	300	300	300	300	300	300
R-squared	0.487	0.640	0.488	0.722	0.499	0.652	0.652	0.904	0.652	0.907	0.660	0.908
α (Long-Short)	-0.00461		-0.00754**		-0.00787**		-0.000735		-7.91e-05		-0.00184	
	(0.00297)		(0.00300)		(0.00312)		(0.00226)		(0.00245)		(0.00235)	

This table presents the performance-evaluation results for our four portfolios, namely buy-bank, buy-firm, sell-bank and sell-firm, constructed only using opportunistic trades. Opportunistic trades are defined as in Cohen, Malloy and Pomorski (2012), that is sales and purchases by insiders with trades in at least 3 consecutive years but in different months. These transactions are allocated to the corresponding portfolio and held for six months, after which portfolios are rebalanced with new trades. The table shows the point estimates and the heteroskedasticity-robust standard errors (in parenthesis) of the factors included in 3, 4 and 5 factor models, namely MKTRF, SMB, HML, MOM, CMA and RMW. These factors are returns to zero-investment portfolios capturing market, size, value, momentum, investment and profitability effects, respectively (see references in the text for details on the construction of these factors). The intercept of the regression line, α, is our variable of interest. The two bottom rows display the α, and its corresponding standard error, estimated on a portfolio long on banks and short on other firms. The symbols *, ** and *** indicate statistical significance at the 10, 5 and 1% levels.

TABLE 7: Intensive-Trading Method (Opportunistic & Routine Trades)

	Opportunistic Trades Only			Opportunistic & Routine Trades		
BANK	-0.183***	-0.265***	-0.277***	-0.249***	-0.326***	-0.312***
	(0.0354)	(0.0391)	(0.0367)	(0.0378)	(0.0406)	(0.0354)
OP	0.0883***	0.0885***	0.0785***	0.0483***	0.0478***	0.0441***
	(0.00512)	(0.00511)	(0.00479)	(0.00594)	(0.00593)	(0.00554)
BANKxOP	-0.0594***	-0.0594***	-0.0480***	-0.0180	-0.0175	-0.0270***
	(0.00853)	(0.00847)	(0.00790)	(0.0125)	(0.0123)	(0.00933)
OS				-0.0467***	-0.0480***	-0.0409***
				(0.00511)	(0.00517)	(0.00482)
BANKxOS				0.0441***	0.0452***	0.0238**
				(0.0117)	(0.0115)	(0.00922)
MV	-0.00858***	-0.0113***	-0.00972***	-0.00880***	-0.0114***	-0.00996***
	(0.00129)	(0.00128)	(0.00125)	(0.00125)	(0.00123)	(0.00120)
BM	0.0172***	0.0241***	0.0281***	0.0183***	0.0246***	0.0286***
	(0.00383)	(0.00438)	(0.00411)	(0.00371)	(0.00427)	(0.00401)
$RET_{t-12,t-2}$	-0.0187***	-0.0209***	-0.0124***	-0.0190***	-0.0212***	-0.0128***
	(0.00326)	(0.00333)	(0.00322)	(0.00318)	(0.00325)	(0.00313)
RET_{t-1}	-0.0684***	-0.0735***	-0.0463***	-0.0681***	-0.0734***	-0.0492***
	(0.0157)	(0.0157)	(0.0156)	(0.0150)	(0.0150)	(0.0150)
BANKxMV	0.00795***	0.0114***	0.0131***	0.00936***	0.0125***	0.0139***
	(0.00203)	(0.00235)	(0.00211)	(0.00206)	(0.00231)	(0.00204)
BANKxBM	-0.0247***	-0.0218**	-0.0501***	-0.0277***	-0.0234***	-0.0490***
	(0.00782)	(0.00862)	(0.00825)	(0.00790)	(0.00842)	(0.00757)
$BANKxRET_{t-12,t-2}$	0.123***	0.116***	0.138***	0.119***	0.112***	0.129***
	(0.0146)	(0.0142)	(0.0141)	(0.0139)	(0.0135)	(0.0143)
$BANKxRET_{t-1}$	0.0622	0.0606	0.127***	0.0675*	0.0670*	0.122***
	(0.0404)	(0.0403)	(0.0376)	(0.0368)	(0.0367)	(0.0348)
MKT. LEV		-0.0254***	-0.0240***		-0.0210**	-0.0200**
		(0.00939)	(0.00863)		(0.00929)	(0.00856)
ROE		0.150***	0.147***		0.148***	0.144***
		(0.0218)	(0.0201)		(0.0205)	(0.0190)
BANKxMKT. LEV		-0.0458	-0.112**		-0.0390	-0.105**
		(0.0695)	(0.0552)		(0.0650)	(0.0531)
BANKxROE		0.0789	-0.156**		0.0928	-0.102
		(0.0770)	(0.0773)		(0.0744)	(0.0647)
CONSTANT	0.224***	0.289***	0.252***	0.273***	0.336***	0.294***
	(0.0259)	(0.0270)	(0.0263)	(0.0253)	(0.0261)	(0.0252)
Observations	134,295	134,295	134,295	143,434	143,434	143,434
R-squared	0.011	0.013	0.121	0.011	0.013	0.122
OP+BANKxOP	0.0289	0.0291	0.0305	0.0303	0.0303	0.0171
p-val	0.0000	0.0000	0.0000	0.00584	0.00505	0.0234
OS+BANKxOS				-0.00263	-0.00283	-0.0172
p-val				0.802	0.784	0.0292

This table presents the results from the intensive-trading method. Observations are stock-months with at least an opportunistic (columns 1-3) and a routine or opportunistic (columns 4-6) trade. Opportunistic and routine trades are defined as in Cohen, Malloy and Pomorski (2012) (See the text for details). OP (OS) is a dummy equal to one for stock-months with at least an opportunistic purchase (sale). Control variables are the same as in Table 4. Standard errors are clustered at the firm level and are reported in parenthesis; 1%, 5% and 10% statistical significance is indicated with ***, ** and * respectively. The bottom of the table reports the linear combination of the insider trading indicators (OP and OS) and their interaction with the bank dummy, as well as the corresponding p-value from a test of statistical significance.

TABLE 8: Normal, Pre-Crisis and Crisis Times (Summary statistics)

	Non-Banks			Banks		
VARIABLES	N	Mean	Std. Dev.	N	Mean	Std. Dev.
Panel A: Performance-evaluation approach						
# of stocks						
Sell - Normal Times	273	1,336	297.0	273	66.96	22.85
Sell- Before Crisis	13	1,661	119.4	13	68.69	10.85
Sell - During Crisis	32	1,359	161.9	32	54.31	6.433
Buy - Normal Times	273	787.8	303.3	273	90.08	31.02
Buy - Before Crisis	13	722.1	79.97	13	103.2	16.42
Buy - During Crisis	32	868.8	181.2	32	111.9	11.85
# of transactions						
Sell - Normal Times	273	22,635	18,570	273	509.4	343.9
Sell- Before Crisis	13	90,433	10,338	13	1,326	341.4
Sell - During Crisis	32	58,150	34,030	32	1,006	484.8
Buy - Normal Times	273	4,858	3,076	273	461.0	191.2
Buy - Before Crisis	13	5,834	2,256	13	864.8	257.9
Buy - During Crisis	32	10,408	5,375	32	982.9	215.7
# of shares (millions)						
Sell - Normal Times	273	587.9	312.9	273	7.477	12.53
Sell- Before Crisis	13	821.0	124.8	13	6.770	1.828
Sell - During Crisis	32	580.0	134.4	32	11.93	14.42
Buy - Normal Times	273	123.5	73.84	273	2.379	3.864
Buy - Before Crisis	13	134.2	25.70	13	1.794	0.618
Buy - During Crisis	32	227.4	86.46	32	4.209	3.314
Value of transactions ($ millions)						
Sell - Normal Times	273	16,582	10,412	273	269.8	522.7
Sell- Before Crisis	13	21,854	3,197	13	243.4	61.30
Sell - During Crisis	32	13,576	4,884	32	231.1	213.3
Buy - Normal Times	273	1,371	1,004	273	31.89	25.95
Buy - Before Crisis	13	1,606	462.7	13	37.13	9.091
Buy - During Crisis	32	2,023	1,007	32	50.78	20.48
Value of transactions (% of market capitalization)						
Sell - Normal Times	273	0.101	0.0799	273	0.0319	0.0280
Sell- Before Crisis	13	0.0201	0.00455	13	0.0116	0.00582
Sell - During Crisis	32	0.0250	0.0112	32	0.0141	0.00943
Buy - Normal Times	273	0.130	0.0950	273	0.0266	0.0331
Buy - Before Crisis	13	0.0711	0.0163	13	0.0170	0.00156
Buy - During Crisis	32	0.0530	0.0154	32	0.0241	0.0117
Average return over six months after transaction date						
Sell - Normal Times	273	0.0108	0.0525	273	0.00932	0.0394
Sell- Before Crisis	13	0.00116	0.0356	13	-0.0111	0.0131
Sell - During Crisis	32	-0.00203	0.0713	32	-0.0110	0.0751
Buy - Normal Times	273	0.0205	0.0528	273	0.0170	0.0362
Buy - Before Crisis	13	0.00558	0.0283	13	-0.0140	0.0344
Buy - During Crisis	32	0.0143	0.0866	32	-0.0145	0.0722
Panel B: Intensive-trading approach						
Net Purchase Dummy						
Normal Times	235,057	0.278	0.448	16,530	0.510	0.500
Before Crisis	6,782	0.146	0.354	444	0.613	0.488
During Crisis	22,393	0.334	0.472	1,737	0.696	0.460
Net Purchase Ratio						
Normal Times	235,057	-15.91	61.07	16,530	5.213	70.27

TABLE 8 (Cont.)

Before Crisis	6,782	-19.99	48.04	444	14.16	59.38
During Crisis	22,393	-9.738	55.93	1,737	19.81	56.02
Net Buyers Ratio						
Normal Times	235,057	-41.82	87.55	16,530	8.329	94.16
Before Crisis	6,782	-67.69	69.85	444	29.29	88.53
During Crisis	22,393	-31.14	91.81	1,737	42.97	84.55

This table shows summary statistics about our four combinations of buy/sell and firm/bank portfolios (Panel A), as well as the variables we use in the intensive-trading approach (Panel B), distinguishing trades executed during normal, pre-crisis and crisis times. Crisis times consists of the months from August 2007 to September 2009, while the pre-crisis period goes from January to July 2007. In Panel A, observations consist of calendar months. The value of transactions as a % of market value and the returns consist of averages across all the trades within a calendar month. The number of transactions and stocks is, respectively, the count of insider trades and different stocks traded in a certain calendar month. Finally, the number of shares and the value of transactions in $ millions are calculated as sums over all the trades within a certain calendar month. In Panel B, observations consist of stock-months with at least a trade by an insider. In both panels, the sample includes trades from January 1990 to December 2015.

TABLE 9: Crisis, Pre-Crisis and Normal Times (Performance-Evaluation Method)

	Buy						Sell					
	Bank	Firm	Bank	Firm	Bank	Firm	Bank	Firm	Bank	Firm	Bank	Firm
MKTRF	0.783***	1.024***	0.740***	0.919***	0.788***	0.919***	0.927***	1.044***	0.914***	1.058***	0.923***	0.935***
	(0.0646)	(0.0449)	(0.0696)	(0.0407)	(0.0693)	(0.0568)	(0.0655)	(0.0345)	(0.0698)	(0.0334)	(0.0645)	(0.0310)
SMB	0.15	0.561***	0.162	0.591***	0.241**	0.500***	-0.180***	0.587***	-0.176***	0.583***	-0.0871	0.528***
	(0.103)	(0.0829)	(0.0985)	(0.0604)	(0.0950)	(0.0769)	(0.0687)	(0.0386)	(0.0656)	(0.0382)	(0.0599)	(0.0462)
HML	0.805***	-0.107	0.759***	-0.219***	0.857***	0.131	0.676***	-0.601***	0.662***	-0.586***	0.753***	-0.354***
	(0.113)	(0.0829)	(0.112)	(0.0733)	(0.152)	(0.101)	(0.102)	(0.0551)	(0.104)	(0.0587)	(0.127)	(0.0514)
MOM			-0.118*	-0.291***					-0.0354	0.0392		
			(0.0632)	(0.0474)					(0.0446)	(0.0289)		
CMA					-0.261	-0.396**					-0.314**	-0.42***
					(0.171)	(0.196)					(0.128)	(0.0910)
RMW					0.221**	-0.258**					0.215**	-0.25***
					(0.110)	(0.123)					(0.0884)	(0.0622)
α	0.00880***	0.0089***	0.0101***	0.0122***	0.00853***	0.0110***	-0.00061	-0.00106	-0.00021	-0.0015	-0.00071	0.00114
	(0.00221)	(0.00189)	(0.00228)	(0.00187)	(0.00220)	(0.00220)	(0.00180)	(0.00115)	(0.00185)	(0.00121)	(0.0018)	(0.00111)
PRE-CRISIS	-0.0289***	-0.00183	-0.0299***	-0.00415	-0.0297***	-0.00227	-0.0113	-0.00043	-0.0115	-0.00012	-0.0122*	-0.00091
	(0.00513)	(0.00665)	(0.00474)	(0.00665)	(0.00495)	(0.00631)	(0.00713)	(0.00269)	(0.00702)	(0.00275)	(0.0072)	(0.00262)
CRISIS	-0.0226*	0.0164**	-0.0259**	0.00809	-0.0241**	0.0158**	-0.0122	-0.0018	-0.0132	-0.00068	-0.014	-0.00247
	(0.0119)	(0.00717)	(0.0118)	(0.00551)	(0.0121)	(0.00694)	(0.0102)	(0.00329)	(0.0101)	(0.00341)	(0.0101)	(0.00262)
R-squared	0.533	0.753	0.541	0.803	0.544	0.766	0.66	0.912	0.66	0.912	0.677	0.926
Observations	312	312	312	312	312	312	312	312	312	312	312	312
CRISIS = PRE-CRISIS (p-val)	0.618	0.0441	0.754	0.13	0.665	0.0376	0.938	0.734	0.89	0.89	0.885	0.647
α +PRE-CRISIS	-0.0201	0.00705	-0.0197	0.00803	-0.0212	0.00876	-0.0119	-0.0015	-0.0118	-0.0016	-0.0129	0.0002
p-val	0.00001	0.262	0.0000	0.206	0.0000	0.141	0.0835	0.545	0.0807	0.516	0.0644	0.924
α +CRISIS	-0.0138	0.0253	-0.0158	0.0203	-0.0156	0.0269	-0.0128	-0.00286	-0.0135	-0.00218	-0.0147	-0.0013
p-val	0.246	0.0002	0.181	0.00005	0.199	0.00004	0.212	0.362	0.189	0.489	0.156	0.583
Long-Short: α	-0.0000832		-0.00205		-0.0025		0.000447		0.00129		-0.00186	
	(0.00263)		(0.00277)		(0.00277)		(0.00214)		(0.00227)		(0.00214)	
Long-Short: PRE-CRISIS	-0.0271***		-0.0257***		-0.0275***		-0.0108		-0.0114*		-0.0112	
	(0.00818)		(0.00855)		(0.00845)		(0.00696)		(0.00674)		(0.00786)	

TABLE 9 (Cont.)

Long-Short: CRISIS	-0.0390***	-0.0340***	-0.0399***	-0.0104	-0.0126	-0.0115
	(0.0126)	(0.0121)	(0.0130)	(0.0102)	(0.0103)	(0.0101)
Long-Short: CRISIS = PRE-CRISIS (p-val)	0.409	0.56	0.401	0.974	0.925	0.985
Long-Short: α +PRE-CRISIS	-0.0272	-0.0277	-0.03	-0.0104	-0.0101	-0.0131
p-val	0.00046	0.00068	0.0002	0.115	0.109	0.0853
Long-Short: α +CRISIS	-0.0391	-0.0361	-0.0424	-0.0099	-0.0113	-0.0133
p-val	0.0016	0.00242	0.001	0.325	0.269	0.191

This table presents the performance-evaluation results for our four portfolios, namely buy-bank, buy-firm, sell-bank, and sell-firm, adding a Pre-Crisis and a Crisis dummy to the asset pricing factors in Table 2. The Crisis (Pre-Crisis) dummy equals one in the calendar months from August 2007 to September 2009 (January to July 2007). The row CRISIS=PRE-CRISIS reports the p-value from a test of the hypothesis that the Crisis and Pre-Crisis dummies are equal. The table also displays the linear combinations α +PRE-CRISIS and α +CRISIS, together with the p-value of a test of statistical significance. The "Long-Short" rows show the estimates and standard errors of α, Crisis and Pre-Crisis dummies, as well as the same tests and linear combinations previously mentioned, using a portfolio long on banks and short on other firms. The symbols *, ** and *** indicate statistical significance at the 10, 5 and 1% levels obtained using robust standard errors.

TABLE 10: Crisis, Pre-Crisis and Normal Times (Intensive-Trading Method)

	Net Purchase Dummy			Net Purchase Ratio			Net Buyers Ratio		
IT	0.0861***	0.0861***	0.0844***	0.0397***	0.0391***	0.0386***	0.0449***	0.0448***	0.0442***
	(0.00368)	(0.00370)	(0.00361)	(0.00208)	(0.00209)	(0.00203)	(0.00192)	(0.00193)	(0.00189)
BANK	-0.121***	-0.182***	-0.239***	-0.217***	-0.288***	-0.321***	-0.153***	-0.213***	-0.267***
	(0.0303)	(0.0345)	(0.0341)	(0.0295)	(0.0334)	(0.0327)	(0.0296)	(0.0336)	(0.0330)
CRISIS	-0.120***	-0.119***		-0.0726***	-0.0704***		-0.0566***	-0.0541***	
	(0.00502)	(0.00503)		(0.00583)	(0.00586)		(0.00698)	(0.00702)	
BANKxCRISIS	-0.0943***	-0.0963***	-0.0888***	-0.157***	-0.159***	-0.122***	-0.168***	-0.171***	-0.127***
	(0.0177)	(0.0181)	(0.0170)	(0.0154)	(0.0153)	(0.0135)	(0.0152)	(0.0152)	(0.0134)
ITxCRISIS	0.127***	0.130***	0.0702***	0.0476***	0.0491***	0.0340***	0.0654***	0.0670***	0.0358***
	(0.0142)	(0.0143)	(0.0114)	(0.00933)	(0.00937)	(0.00774)	(0.00736)	(0.00739)	(0.00590)
BANKxIT	-0.0640***	-0.0642***	-0.0562***	-0.0297***	-0.0293***	-0.0259***	-0.0319***	-0.0319***	-0.0282***
	(0.00607)	(0.00610)	(0.00584)	(0.00361)	(0.00364)	(0.00350)	(0.00323)	(0.00324)	(0.00310)
BANKxITxCRISIS	-0.151***	-0.152***	-0.0777***	-0.0449**	-0.0445**	-0.0248	-0.0788***	-0.0794***	-0.0384**
	(0.0298)	(0.0298)	(0.0280)	(0.0218)	(0.0216)	(0.0208)	(0.0165)	(0.0165)	(0.0154)
PRECRISIS	-0.0713***	-0.0716***		-0.104***	-0.104***		-0.137***	-0.138***	
	(0.00658)	(0.00654)		(0.00649)	(0.00649)		(0.00796)	(0.00794)	
BANKxPRECRISIS	-0.137***	-0.132***	-0.140***	-0.132***	-0.129***	-0.119***	-0.0945***	-0.0902***	-0.0884***
	(0.0201)	(0.0204)	(0.0193)	(0.0144)	(0.0146)	(0.0140)	(0.0150)	(0.0152)	(0.0147)
ITxPRECRISIS	-0.128***	-0.129***	-0.118***	-0.0382***	-0.0387***	-0.0368***	-0.0692***	-0.0698***	-0.0642***
	(0.0152)	(0.0152)	(0.0150)	(0.00919)	(0.00918)	(0.00899)	(0.00790)	(0.00787)	(0.00779)
BANKxITxPRECRISIS	0.0762***	0.0745***	0.0981***	0.0246	0.0239	0.0383**	0.0398***	0.0391***	0.0532***
	(0.0265)	(0.0265)	(0.0257)	(0.0165)	(0.0165)	(0.0164)	(0.0136)	(0.0136)	(0.0134)
MV	-0.0101***	-0.0135***	-0.0127***	-0.0139***	-0.0175***	-0.0159***	-0.0100***	-0.0134***	-0.0126***
	(0.00105)	(0.00105)	(0.00105)	(0.00106)	(0.00106)	(0.00105)	(0.00105)	(0.00105)	(0.00105)
BM	0.0246***	0.0342***	0.0397***	0.0187***	0.0318***	0.0375***	0.0250***	0.0340***	0.0396***
	(0.00287)	(0.00336)	(0.00325)	(0.00285)	(0.00335)	(0.00323)	(0.00288)	(0.00336)	(0.00325)
$RET_{t-12,t-2}$	-0.0249***	-0.0280***	-0.0157***	-0.0278***	-0.0308***	-0.0182***	-0.0248***	-0.0279***	-0.0156***
	(0.00261)	(0.00263)	(0.00250)	(0.00266)	(0.00268)	(0.00253)	(0.00261)	(0.00263)	(0.00250)
RET_{t-1}	-0.0567***	-0.0659***	-0.0347***	-0.0795***	-0.0884***	-0.0517***	-0.0553***	-0.0646***	-0.0335***
	(0.0119)	(0.0118)	(0.0120)	(0.0121)	(0.0119)	(0.0120)	(0.0119)	(0.0118)	(0.0120)
BANKxMV	0.00714***	0.00863***	0.0128***	0.0105***	0.0120***	0.0153***	0.00718***	0.00864***	0.0129***
	(0.00170)	(0.00198)	(0.00191)	(0.00169)	(0.00195)	(0.00187)	(0.00169)	(0.00197)	(0.00191)

TABLE 10 (Cont.)

BANKxBM	0.00103	5.67e-05	-0.0368***	0.00812	0.00363	-0.0321***	0.000528	8.72e-05	-0.0370***
	(0.00740)	(0.00744)	(0.00674)	(0.00736)	(0.00743)	(0.00671)	(0.00740)	(0.00744)	(0.00672)
BANKxRET$_{t-12,t-2}$	0.0364***	0.0335***	0.0810***	0.0387***	0.0355***	0.0824***	0.0366***	0.0337***	0.0813***
	(0.0114)	(0.0113)	(0.0119)	(0.0114)	(0.0113)	(0.0119)	(0.0114)	(0.0113)	(0.0119)
BANKxRET$_{t-1}$	-0.0464	-0.0438	0.0645**	-0.0282	-0.0261	0.0794***	-0.0460	-0.0433	0.0653**
	(0.0285)	(0.0282)	(0.0280)	(0.0283)	(0.0281)	(0.0276)	(0.0285)	(0.0282)	(0.0280)
		(0.0584)	(0.0492)		(0.0575)	(0.0477)		(0.0585)	(0.0492)
CONSTANT	0.261***	0.341***	0.304***	0.375***	0.466***	0.413***	0.302***	0.380***	0.345***
	(0.0212)	(0.0223)	(0.0222)	(0.0213)	(0.0224)	(0.0221)	(0.0211)	(0.0222)	(0.0220)
Additional Controls	NO	YES	YES	NO	YES	YES	NO	YES	YES
Time Fixed Effects	NO	NO	YES	NO	NO	YES	NO	NO	YES
Observations	280,229	280,229	280,229	280,229	280,229	280,229	280,229	280,229	280,229
R-squared	0.015	0.017	0.098	0.011	0.013	0.095	0.015	0.017	0.098
IT+BANKxIT	0.0221	0.0219	0.0281	0.0100	0.00981	0.0127	0.0130	0.0130	0.0159
p-val	0.0000	0.0000	0.0000	0.0007	0.0009	0.0000	0.0000	0.0000	0.0000
IT+BANKxIT+ITxPRECRISIS+BANKxITxPRECRISIS	-0.0295	-0.0321	0.00856	-0.00352	-0.00498	0.0141	-0.0164	-0.0177	0.00496
p-val	0.186	0.150	0.692	0.800	0.719	0.311	0.152	0.121	0.660
IT+BANKxIT+ITxCRISIS+BANKxITxCRISIS	-0.0016	0.00046	0.0206	0.0128	0.0144	0.0219	-0.0004	0.00056	0.0133
p-val	0.948	0.985	0.379	0.499	0.442	0.231	0.975	0.968	0.311
BANKxITxPRECRISIS+ITxPRECRISIS	-0.0516	-0.0540	-0.0196	-0.0135	-0.0148	0.0014	-0.0294	-0.0307	-0.0110
p-val	0.0176	0.0129	0.349	0.325	0.280	0.917	0.0082	0.0057	0.315
BANKxITxCRISIS+ITxCRISIS	-0.0237	-0.0215	-0.0075	0.0028	0.0045	0.0092	-0.0134	-0.0124	-0.0025
p-val	0.365	0.412	0.762	0.889	0.816	0.629	0.365	0.401	0.853
BANKxIT+BANKxITxPRECRISIS	0.0121	0.0103	0.0418	-0.00510	-0.00533	0.0123	0.00787	0.00722	0.0250
p-val	0.651	0.701	0.109	0.758	0.746	0.455	0.569	0.601	0.0662
BANKxIT+BANKxITxCRISIS	-0.215	-0.216	-0.134	-0.0746	-0.0738	-0.0507	-0.111	-0.111	-0.0666
p-val	0.0000	0.0000	0.0000	0.00036	0.000381	0.0109	0.0000	0.0000	0.0000

This table presents the results on the time variation in bank opacity using the intensive-trading method. Observations are stock-months with at least a trade by an insider. Our variables of interest are trading intensity (IT), as measured either by the Net Purchase Dummy (col. (1)-(3)), Net Purchase Ratio (col. (4)-(6)) and Net Buyers Ratio (col. (7)-(9)), as well as its interaction with a bank dummy and time dummy. Two time dummies are included: One capturing months during the period August 2007-September 2009 (crisis) and another the months from January to July 2007 (pre-crisis). Control variables are the same as in Table 4. Additional controls include ROE, Market Leverage and their interaction with the bank dummy. Standard errors are clustered at the firm level and are reported in parenthesis; 1%, 5% and 10% statistical significance is indicated with ***, ** and * respectively. The bottom of the table reports a set of linear combination of the insider trading indicators and their interaction with the bank and time dummies (see Section 7.2 for details), as well as the corresponding p-value from a test of statistical significance.

TABLE 11: Balance Sheet Characteristics (Intensive-Trading Method)

	Bank Sample			Banks & Firms - Joint Estimation					
				Banks	Firms	Banks	Firms	Banks	Firms
P	0.024***	0.019***	0.020***	0.0245***	0.0877***	0.0191**	0.0877***	0.0201**	0.0897***
	(0.00457)	(0.00709)	(0.00665)	(0.00475)	(0.00251)	(0.00891)	(0.00251)	(0.00862)	(0.00263)
LOANS	-0.00525	-0.000302	-0.000248	-0.00525		-0.000302		-0.000248	
	(0.00585)	(0.00860)	(0.00851)	(0.00327)		(0.00807)		(0.00803)	
PxLOANS	0.00146	-0.00290	-0.00279	0.00146		-0.0029		-0.00279	
	(0.0108)	(0.0159)	(0.0159)	(0.00416)		(0.00852)		(0.00847)	
MKT.LEV	0.00652	0.00251	0.00243	0.0065***		0.00251		0.00243	
	(0.00447)	(0.00783)	(0.00776)	(0.00245)		(0.00655)		(0.00651)	
PxMKT.LEV	0.000575	0.00408	0.00403	0.000575		0.00408		0.00403	
	(0.00662)	(0.0101)	(0.0100)	(0.00309)		(0.00678)		(0.00674)	
TRADING	-0.0106	0.00154	0.000767	-0.0106		0.00154		0.000767	
	(0.0104)	(0.0172)	(0.0167)	(0.00730)		(0.0296)		(0.0295)	
PxTRADING	-0.0170	-0.0641**	-0.0625**	-0.017		-0.0641*		-0.0625*	
	(0.0157)	(0.0299)	(0.0288)	(0.0107)		(0.0356)		(0.0353)	
DEPOSITS	0.0467	-0.0252	-0.0225	0.0467*		-0.0252		-0.0225	
	(0.0354)	(0.0329)	(0.0330)	(0.0261)		(0.0433)		(0.0431)	
PxDEPOSITS	-0.0644	-0.0115	-0.0154	-0.0644*		-0.0115		-0.0154	
	(0.0401)	(0.0587)	(0.0553)	(0.0375)		(0.0645)		(0.0632)	
LIQUIDITY	-0.0254	0.0191	0.0200	-0.0254		0.0191		0.02	
	(0.0394)	(0.0533)	(0.0529)	(0.0314)		(0.0612)		(0.0610)	
PxLIQUIDITY	0.0308	0.0371	0.0370	0.0308		0.0371		0.037	
	(0.0898)	(0.142)	(0.143)	(0.0466)		(0.0820)		(0.0818)	
LOAN LOSS ALL.	0.287	-0.889	-0.947	0.287		-0.889		-0.947	
	(0.411)	(0.848)	(0.844)	(0.376)		(0.949)		(0.941)	
PxLOAN LOSS ALL.	-0.00614	-2.004	-1.942	-0.00614		-2.004		-1.942	
	(0.923)	(2.179)	(2.112)	(0.541)		(1.277)		(1.259)	
DIVERSIF.	0.0209	-0.0157	-0.0197	0.0209		-0.0157		-0.0197	
	(0.0280)	(0.0399)	(0.0396)	(0.0249)		(0.0416)		(0.0401)	
PxDIVERSIF.	-0.00265	0.00825	0.0136	-0.00265		0.00825		0.0136	
	(0.0373)	(0.0485)	(0.0430)	(0.0357)		(0.0561)		(0.0540)	
LOAN GROWTH	-0.0123	0.0136	0.0109	-0.0123		0.0136		0.0109	
	(0.0146)	(0.0243)	(0.0234)	(0.0136)		(0.0269)		(0.0264)	
PxLOAN GROWTH	-0.00726	-0.0409	-0.0413	-0.00726		-0.0409		-0.0413	
	(0.0184)	(0.0423)	(0.0403)	(0.0185)		(0.0388)		(0.0382)	
SECURIT.ASSETS		-0.00296				-0.00296			
		(0.0105)				(0.0142)			
PxSECURIT.ASSETS		0.00856				0.00856			
		(0.0204)				(0.0214)			
SECURIT.INCOME		-0.102*				-0.102			
		(0.0574)				(0.215)			
PxSECURIT.INCOME		-0.202*				-0.202			
		(0.118)				(0.369)			
MV	0.000556	-0.00221	-0.00219	0.000556	-0.0095***	-0.00221	-0.0095***	-0.00219	-0.0075***
	(0.00221)	(0.00340)	(0.00351)	(0.00155)	(0.000609)	(0.00305)	(0.000609)	(0.00270)	(0.000617)
BM	-0.0347	-0.0374	-0.0376	-0.0347***	0.03***	-0.037***	0.0305***	-0.038***	0.0119***
	(0.0275)	(0.0457)	(0.0447)	(0.00789)	(0.00147)	(0.0133)	(0.00147)	(0.0131)	(0.00142)

TABLE 11 (Cont.)

$RET_{t-12,t-2}$	0.0104	0.00744	0.00715	0.0104	-0.0121***	0.00744	-0.0121***	0.00715	-0.0153***
	(0.0129)	(0.0226)	(0.0227)	(0.00861)	(0.00131)	(0.0155)	(0.00131)	(0.0155)	(0.00142)
RET_{t-1}	-0.0760*	-0.0422	-0.0423	-0.0760***	-0.0237***	-0.0422	-0.0237***	-0.0423	-0.0537***
	(0.0447)	(0.0802)	(0.0803)	(0.0250)	(0.00629)	(0.0430)	(0.00629)	(0.0429)	(0.00668)
CONSTANT	0.0414	0.0386	0.0379	0.489***	0.484***	0.125	0.484***	0.124	0.414***
	(0.0346)	(0.0530)	(0.0564)	(0.0359)	(0.0247)	(0.0916)	(0.0247)	(0.0902)	(0.0231)
Observations	15,519	7,676	7,676	15519	261886	7676	261886	7676	157608
R-squared	0.274	0.205	0.204	0.259	0.095	0.184	0.095	0.184	0.182
Time Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
P+PxLOANS	0.0288	0.0106	0.0119	0.0288		0.0106		0.0119	
p-val	0.343	0.815	0.796	0.337		0.812		0.793	
P+PxTRADING	0.0245	0.0190	0.0200	0.0245		0.0190		0.0200	
p-val	0.0000	0.00765	0.00287	0.0000		0.00641		0.00228	
P+PxMKT.LEV	0.0267	0.0346	0.0353	0.0267		0.0346		0.0353	
p-val	0.325	0.395	0.374	0.319		0.387		0.367	
P_{bank} - P_{firm}				0.0000		0.0000		0.0000	
P_{bank} + PxLOANS - P_{firm}				0.0507		0.085		0.0872	
P_{bank} + PxTRADING - P_{firm}				0.0237		0.185		0.167	
P_{bank} + PxMKT.LEV - P_{firm}				0.00000		0.00000		0.0000	

This table presents the results on the within-bank variation in bank opacity using the intensive-trading method. Observations are stock-months with at least a trade by an insider. Columns (1)-(3) report the estimates from the bank sample, while the joint estimates on the bank and firm samples are displayed in columns (4)-(9). Our variables of interest are the Net Purchase Dummy (P) and, for the bank sample, its interaction with the following bank balance sheet ratios: Loans to market capitalization, trading assets to market capitalization and market leverage, calculated as the sum of market capitalization and book value of liabilities divided by market capitalization. Control variables include the log of market capitalization (MV), the log of book to market ratio (BM), cumulative stock returns over the months t-12 to t-2 ($RET_{t-12, t-2}$) and stock return in month t-1 (RET_{t-1}). Month fixed effects are included where indicated. In the bank sample, we also control for the balance sheet ratios in set B (see equation (3) and Section 8.1). All balance sheet ratios are expressed as deviations from the quarterly median of the distribution across all listed banks. Standard errors are clustered at the firm level and are reported in parenthesis; 1%, 5% and 10% statistical significance is indicated with ***, ** and * respectively. The bottom of the table reports the linear combination of the Net Purchase Dummy (P) and its interaction with our three balance sheet ratios of interest evaluated at the (average) 75^{th} percentile of their distribution across all listed banks, as well as the corresponding p-value under the null hypothesis of these linear combinations being zero. The last four rows display the p-value from a test of equality of the Net Purchase Dummy, as well as its linear combinations with our variables of interest, estimated on the bank and firm samples.

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