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The impact of Becoming Primary Dealer:

A Cross-Country Analysis

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ABSTRACT

A primary dealer system is an arrangement between the sovereign debt manager and a group of financial institutions, also called dealers, to strengthen the functions, operations and the development of primary and secondary markets for government securities.

Due to the recent sovereign debt crisis and the increasing urgency of efficiently placing rising government debt, primary dealers have acquired a progressively important role. This research focuses on the impact of becoming a primary dealer for a sample of banks operating in 19 different countries.

Becoming a primary dealer has positive effects on the reputation and reliability of the banks that are selected. They become an important counterparty of both the sovereign debt manager for profitable debt management operations and the national central bank for monetary policies. Using an event study, I confirm the hypothesis that financial markets positively value the role of primary dealers to such an extent that dealers experience a significant abnormal stock returns in the two weeks following the appointment.

Moreover, primary dealers help the government to transport liquidity into other markets. They buy government securities at auction and hold the securities in inventory until they find an acquirer in the secondary market. They absorb the imbalances of the transaction in their own balance sheets, carrying large securities inventory.

Using a difference-in-difference model, I also confirm the expectation of dealers ‘balance sheet expansion. Results shows that becoming a primary dealer brings higher growth in total assets compared to control banks. No evidence points in the direction of more liquid primary dealers compared to control banks.

Keywords: Primary Dealers, Difference-in-Difference, Event Study, Credit Rating

TABLE OF CONTENTS

ABSTRACT ii
TABLE OF CONTENTS iii
LIST OF TABLES iv
LIST OF FIGURES iv
1 Introduction 1
1.1 Primary Dealers 1
1.2 Research Hypotheses and Conceptual Framework 3
2 Literature Review 6
2.1 Primary Dealer Systems 6
3 Data Description 8
3.1 Primary Dealers 8
4 Event Study 12
4.1 Event Study Methodology 12
4.1.1 Market Model Method 13
4.1.2 Significance Tests 14
4.2 Event Study Results 15
5 Difference-in-Difference Model 19
5.1 Defining Treated and Control Groups 19
5.2 The Model and Variables 20
5.3 Difference-in-Difference Model Results 22
6 Limitations and Further Research 33
7 Conclusions 34
REFERENCES 36
APPENDIX A: Original Methodology and Credit Rating Model 40
A.1 Credit Ratings Estimated Model 42
APPENDIX B: List of Countries 47
APPENDIX C: Event Study 48
C.1Test Statistics 48
APPENDIX D: Credit Ratings Mapping 52
APPENDIX E: Variable Definitions 53
APPENDIX F: Difference-in-Difference Graphs 54

LIST OF TABLES

Table 1: Sample Derivation 10
Table 2: Summary Statistics of Primary Dealers 11
Table 3: Cross-sectional properties of Alternative Performance Measures at day ‘0’ 15
Table 4: Cumulative Abnormal Primary Dealers’ Return 16
Table 5: *Growth of Total Assets*: Difference-in-Difference Estimates 23
Table 6: *Retail Deposits*: Difference-in-Difference Estimates 25
Table 7: *Non-Deposits Short-Term Funding*: Difference-in-Difference Estimates 27
Table 8: *Interbank Funding*: Difference-in-Difference Estimates 29
Table 9: *Long-Term Funding*: Difference-in-Difference Estimates 31
Table 10: Credit Rating Estimated Model 44
Table 11: Marginal Effects of Solvency conditional on Country Credit rating 45
Table 12: Distance between Predicted and Observed Ratings 45
Table 13: List of Countries 47
Table 14: Abnormal Returns: Primary Dealers 49
Table 15: Cumulative Abnormal Returns of Primary Dealers 51
Table 16: Mapped Credit ratings 52
Table 17: Variable Description 53

LIST OF FIGURES

Figure 1: Average Abnormal Cumulative Returns over Time 18
Figure 2: Difference in Difference estimation, graphical explanation 20
Figure 3: Estimated impact of becoming primary dealer on *Growth of Total Assets* 24
Figure 4: Estimated impact of becoming primary dealer on *Retail Deposits* 26
Figure 5: Estimated impact of becoming primary dealer on *Non-Deposits Short-Term F* 28
Figure 6: Estimated impact of becoming primary dealer on *Interbank Funding* 30
Figure 7: Estimated impact of becoming primary dealer on *Long-term Funding* 32
Figure 8: Frequency Distribution of Credit Rating Regression Residuals 46
Figure 9: Plot of Year-by-year *Growth of Total Assets* 54
Figure 10: Plot of Year-by-year *Retail Deposits* 54
Figure 11: Plot of Year-by-year *Non-Deposits Short-Term Funding* 55
Figure 12: Plot of Year-by-year *Interbank Funding* 55
Figure 13: Plot of Year-by-year *Long-Term Funding* 56

1 Introduction

Government deficit financing is one of the main reasons to develop an efficient government debt market (Turner, 2002). Before the 80s, local banks used to hold large portions of government paper[1], satisfying governments' borrowing needs. In addition, high inflation made the debt financing cheaper for many countries and foreign borrowing was a valuable financing channel since exchange rate risk was a limited risk under fixed exchange rates system. The increasingly burdensome public debt of many countries, the liberalisation and integration of financial market and the following global capital inflows, the adoption of anti-inflationary policies and floating exchange rates had changed the shape and needs of government debt markets over the years. Government were increasingly relying on domestic markets to borrow money and central banks needed to closer monitor inflation levels and steer interest rates when necessary to sterilize large capital inflows[2].

The economic instability that we have faced over the last years led to a massive growth of fiscal deficit which in turn led to higher money supply, weak exchange rate, uncertainty and low interest among investors for new issuances of Treasuries. Therefore, the increasing sophistication of financial markets and, in turn, of government debt markets, reopened the discussion about mechanisms to conduct effective monetary policies and to place new issues of Treasuries. (World Bank and IMF, 2001). Generally, the bond market has been overlooked and less scrutinized than the equity one[3].

1.1 Primary Dealers

A milestone in the government bond market has been the introduction of primary dealerships. Federal Reserve introduced the primary dealer system for the first time in history during the 60s. It spread in Europe during the 80s and to emerging markets in the 90s. A primary dealer system is an arrangement between the sovereign debt manager and a group of financial

[1] This was mainly done to meet the strict reserve requirements by the government, see Turner (2002).

[2] Sterilization of large capital inflows became a difficult process during the early 90s since bond markets were not well developed. Central banks had at disposal only short-term instruments to conduct open market operations. Increasing the supply of short-term paper means driving up short-term interest rates and consequently attracting further flows into such paper. This can bias the structure of inflows towards the short end.

[3] Herring and Chatusripitak (2001) provides a good summary regarding the importance of well-developed bond markets.

institutions, also called dealers, to strengthen the functions, operations and the development of primary and secondary markets for government securities.

The World Bank, in its primary dealer's handbook, outlines multiple benefits of establishing such a system: (a) to create a stable demand for government bonds and enlarge the customer base: primary dealers are obliged to submit a certain number of successful bids at auctions of government bonds[4]. Fleming (2007) finds that U.S. primary dealers acquire, on average, 70% of Treasuries issued by the Federal Reserve between 2003 and 2005. This allows the government to participate less to the market and for larger amounts; (b) to continuously quote bid and ask prices in the secondary market, enhancing its liquidity and eventually decrease the government cost of funding[5]. Primary dealers actively promote government securities in the secondary market, trying to re-sell the portfolio of government securities at a premium. In some markets, they are obliged to have a minimum turnover ratio and a minimum success ratio; (c) to provide advisory services to the government on debt strategy and market development (qualitative and quantitative reports are submitted on a frequent basis).

For these services, the dealers receive some privileges in exchange as rents, affecting government costs for new issuances. Despite these additional costs for the issuers, the use of primary dealers in financial markets is popular all around the world and supported by extensive literature[6]. A survey conducted by Arnone and Iden (2003) finds that 75% of the surveyed countries implemented the primary dealership, suggesting that most of the countries believe in the high potential of intermediaries also in the market for government securities. The preference for primary dealerships and their use over other systems is due to the matching role that dealers play: they guarantee fully subscription, excluding the possibility of failed issuances and reducing operational risk. An under subscribed issuance of government bonds implies higher costs for future issuances and, in some cases, sovereign downgrades. (Sareen, 2009).

If on the one hand, the limited number of dealers interacting with the government reduces the burden of administrative and monitoring costs, on the other, restricting the number of participants only to primary dealers, may negatively affect the competitiveness of the bidding process during sovereign debt issuances.

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[4] They have to buy a minimum percentage of the total amount either at each auction or over a limited period.

[5] Most debt manager set a maximum spread for the quoted prices.

[6] Even though primary dealerships are not a precondition for a well-functioning government securities market, they are fundamental to support the market development strategy for many countries.

Despite criticisms, the increasing needs for sovereign debt financing support the use of primary dealer systems. Arnone and Iden (2003) show a positive relation between the size of public debt and the desirability of the primary dealership. The authors report the privileges granted by each country to the dealers. Most of the countries concede primary dealers the right to become exclusive counterparties for open market operations with the central bank and access to credit facilities and exclusive access to primary auction and non-competitive bidding.

1.2 Research Hypotheses and Conceptual Framework

Due to the recent sovereign debt crisis and the increasing urgency of efficiently placing rising government debt, primary dealers have acquired a progressively important role. This research focuses on the impact of becoming a primary dealer for a sample of banks operating in 19 different countries. The first hypothesis of the research is defined as follow:

H1: Banks exhibit abnormal stock return when becoming members of the system (i.e. primary dealers) and the value added by the abnormal return is persistent.

I expect this first hypothesis to hold because of the advantages that the banks derive from becoming primary dealers[7]. The announcement has positive effects on the reputation and reliability of the banks that are selected to be primary dealers[8]. They become an important counterparty of both the sovereign debt manager for profitable debt management operations and the national central bank for monetary policies. Additionally, they have assisted access to central bank lending facilities and access to inside information about the government bonds market and changes in monetary policy. Being part of the primary dealer system reduces the overall risk of running operations since the government provides an implicit guarantee in case of default or financial distress. For instance, in 2008, the U.S. government approved the Primary Dealer Credit Facility in response to the subprime mortgage crisis. All the U.S banks that were considered "too big to fail" were Fed's primary dealers. This mechanism can be a source of

[7]Primary dealers may be able to extract rent from the government but at the same time, they have important obligations to meet such as participating in all auctions of government debt and helping to execute open market operations to carry out monetary policies. See Federal Reserve website for a complete overview of its primary dealers business standards *https://www.newyorkfed.org/markets/pridealers_policies.html*

[8]This important recognition is used for marketing purposes by the banks to enlarge their customer base especially among institutional investors.

moral hazard: primary dealers may run additional risk given the perception that governments will follow the "whatever it takes" principle to assist them in case of financial distress or failure. I conduct an event study to determine the effects on the stock prices of the banks around the announcement and/or effective entrance dates into the primary dealer system.

Finally, primary dealers help the government to transport liquidity into other markets. Primary dealers buy government securities at auction and hold the securities in inventory until they find an acquirer in the secondary market. They absorb the imbalances of the transaction in their own balance sheets, carrying large securities inventory (Harris, 2003). Fleming and Rosenberg (2008) report that in the third quarter of 2006, U.S. primary dealers had a daily average Treasury trading volume of $291 billion with customer and $220 billion with other dealers demonstrating that they are the leading market makers for Treasuries. Moreover, they show how dealers' balance sheet remain distorted for at least one week after the auction took place. Dealers expand their inventory during auction weeks buying government securities when prices are depressed and then sell these securities later on when prices recover. Therefore, I expect that when a bank becomes primary dealer, it holds larger and more liquid inventories of securities. The impact permanently changes the structure of the balance sheet. The second hypothesis of the research follows:

H2: Primary dealers expand their balance sheet, becoming more liquid institutions.

To test this last hypothesis, I use the difference-in-difference technique and I follow a specific framework that is discussed in details in section 5.

History teaches that liquidity may evaporate suddenly without a rationale. Therefore, the role of market makers like primary dealers is fundamental to keep the market alive especially during periods of illiquidity when they work as a buffer and correct market distortions. Holding the inventory is a source of risk for the dealer since this operation increases the capital charges on the stale inventory[9].

[9] These considerations are in favour of an adequate compensation for banks. However, it is important to make a clarification: government bonds are liquid financial instruments and more easily convertible into cash than other type of securities.

The rest of the paper proceeds as follows. Section 2 reviews the past and ongoing debate about primary dealerships, illustrating the outstanding literature and presenting the new perspective brought by this research. Section 3 describes the data sample, variables and source of data. Section 4 and 5 presents the methodologies used in the study along with the results. Section 6 presents the main limitations and suggestions for further research. Conclusions follow.

2 Literature Review

2.1 Primary Dealer Systems

Market microstructure has been widely discussed in the literature. The dynamics of the markets determine asset prices, transaction costs and trading volume. Demesetz (1968) was first to present the role of intermediaries (i.e dealers). During the 80s and 90s many countries reformed their government securities market assuming an active role in the formation of institutional structures. The costs of raising funds by government agencies is determined by the structure and efficiency of the markets. Therefore, it is best interest of the authorities to develop liquid, deep and well-functioning markets for government securities and promote efficient market structures (Dattels & Peter, 1997).

Most of the outstanding literature on primary dealerships analyses the impact of such systems from the government point of view, describing whether they improve the quality, smoothness and profitability of the debt issuances and provides suggestions on how the primary dealerships can be ameliorated.

Breuer (1999) describes the first analytical analysis in the field. In his paper the author implements a model to compare different primary and secondary market interventions concluding that primary dealerships add value and improve government revenues during auctions only in case of limited competition among heterogeneous primary dealers.

Regarding competition, the World Bank suggests an adequate number of primary dealers to range between five and twenty-five. Five is the minimum number to ensure competition[10].

Sareen (2009) links market microstructure literature with theoretical and empirical analysis of treasury markets. The author studies the bidding process of Canadian primary dealership suggesting that the participation of primary dealers to debt issuances guarantees fully subscription excluding the possibility of failed issuances. This latter result is not a "free lunch" for the government: the author notes that a compensation for the provided intermediation services is necessary to obtain such a positive outcome[11]. There has been a long debate over the appropriate compensation for primary dealers. Debt management offices claim that primary dealers are not always fair bidders in government debt auctions, substantially reducing the

[10] See more details at http://siteresources.worldbank.org/FINANCIALSECTOR/Resources/Primary_Dealer_Systems_Handbook.pdf

[11] As discussed in Sareen (2009), the rent extracted by the primary dealers derive from reduced competition and increased probability of collusion during auctions.

potential revenue for the government and extracting rent. Moreover, they are not quoting bid and ask prices in the way they are supposed to, making the market not liquid enough. Primary dealers respond that the compensation they receive is not adequate in relation to the risky and expensive business they have to do[12].

There is scarce outstanding literature analysing the effects of primary dealerships on the bank side and, if existing, literature presents a qualitative description of the systems rather than quantitative. The advantages and disadvantages of primary dealerships, privileges and obligations are the main content in McConnachie & Robin (1996).

A more complete overview is given in Arnone & Ugolini (2005) and Arnone & Iden (2003). The authors propose evidence in support of primary dealer systems, exhibiting the results of surveys based on individual country experiences. Their research is the closest to mine in the literature since we both try to provide a global picture of the primary dealerships.

More precisely, I focus on bank side and, as far as I am concerned, there is little or no existing literature on examining the impact of becoming a primary dealer in such a global way (19 countries). There are no previous studies, which conduct an event study on primary dealers and analyse them at balance sheet level for such a large number of countries.

Finally, this study adds a significant and unique extension: using a regression model, I try to explain primary dealers' credit ratings published by agencies and to estimate them if not publicly available. To my best knowledge, this is something not present in the literature and it may be useful for future research since credit ratings of some primary dealers are not easily accessible, if ever published[13]. Most of the outstanding literature about credit risk focuses on probability of default models because mimicking credit ratings implies the identification of companies 'default-related factors. Altman (1968) sets the guidelines for predicting corporate default based on financial ratios since credit ratings are linked to probability of default and the latter to financial statement information. Following the methodology presented by Cardoso et al. (2013), I use a so-called shadow-rating model, which approximate credit ratings using companies' financial data.

[12] More information about this debate can be found on these background notes of Gemloc (Global Emerging Market Local Currency Bond), a program sponsored by the World Bank, at http://siteresources.worldbank.org/FINANCIALSECTOR/Resources/Primary_Dealer_Systems_Handbook.pdf

[13] As mention in Cardoso et al. (2013), only approximately 3,000 companies are rated by external agencies and most of them are U.S. based.

3 Data Description

3.1 Primary Dealers

The list of primary dealers is provided by my supervisor as result of a selection performed by another student. The original source are central banks or finance ministries of countries which accepted to provide information related to primary dealers. Before starting the analysis, I perform a revision of the provided dataset. Hereafter, I will name the provided dataset as reference dataset and the one eventually used in this research as actual dataset.

The main improvement that I bring regards the selection of banks whit real availability of data and with long history of data. In Bankscope[14], each bank is linked with one or more financial statement formats identified by different so-called consolidation codes. Each code identifies different types of data: a) financial statements consolidated using GAAP and others using IFRS; b) formats including long history and others only shorter history; c) consolidated and unconsolidated financial statements. This gave me the opportunity of selecting, among all consolidation formats, the one which had the longest history (up to 15 years). Not doing this would have been a big limitation for the research: only using the longest available historical data for each bank I was able to cover the minimum necessary number of observations around dates of interest (banks becoming primary dealers). Without this extension, for most of the banks I would not had before and after observations, making the difference-in-difference analysis not reliable. Therefore, I not only reviewed the list of banks but I also picked the best format of available data for each bank.

When comparing the reference dataset with the actual one, there are two main differences: a) the overall number of banks; b) the format of the financial information available for each bank. The former difference is due to the decision of dropping some dealers depending on the real availability of data in Bankscope. Dealers with missing information in Banksocpe are dropped and some others, like Turkish primary dealers, are dropped because of unreliable data. In few cases, the actual dataset includes more dealers than the reference one. This is because, when reviewing the original lists sent by central banks or finance ministries, I found some extra banks which were not considered at all in the reference dataset. Table 1 shows how the actual sample of this research is derived at country level.

[14] Bankscope (by Bureau Van Dijk) is the database used for this research since it is the biggest and most reliable database for both public and private banks all around the world.

Eventually, the sample is composed of 147 primary dealers from 19 different countries. The resulting dataset is unbalanced and ranges from 1988 to 2015.
Bankscope is also source of credit ratings for some banks and only for selected years. I focus only on the ratings issued by S&P, Fitch and Moody's. Following the criteria defined by the literature (Adelino & Ferreira, 2016) I retrieve the long-term credit rating for each bank, crosschecking the data from the three different agencies and only for the years when banks become primary dealers.
Primary Dealers' daily stock prices are collected from Datastream (Thomson Reuters) for 66 dealers at the point in time when they enter the primary dealer system. In this step, I lose data about 81 dealers for two main reasons. Firstly, some of them are unlisted or delisted banks in the time period that I need. Secondly, for some banks of the sample I do not have the accurate dates when they became primary dealers. Entrance dates are retrieved from the press archive or official bulletins of central banks and ministry of finances. I use ISIN codes to identify the banks. Market index data are collected from Datastream as well.

Table 1

Sample Derivation

This table shows how the actual sample of this research is derived. It compares the reference dataset with the actual one. Not all countries are represented in both datasets. The last column shows whether primary dealers have been dropped or added with respect to the reference dataset.

Country	**Reference Sample**	**Actual Sample**	**Δ**
	# Dealers	# Dealers	(Dropped)/Added
BE	18	11	(7)
BG	18	15	(3)
CZ	13	14	1
DK	8	6	(2)
ES	0	1	1
GR	5	5	0
HK	7	6	(1)
HU	15	11	(4)
IT	18	14	(4)
LT	9	9	0
LV	0	4	4
MX	12	11	(1)
NL	12	4	(8)
NO	4	7	3
PT	10	10	0
SE	0	1	1
SG	0	5	5
SI	6	6	0
ZA	10	7	(3)
TR	20	0	(20)
Total	**185**	**147**	**(38)**

Table 2 reports summary statistics of primary dealers for selected variables related to banks' balance sheets[15]. I make a distinction between two groups: a) 90 banks, which entered into the system in the introduction year (early joiner hereafter) and b) 58 banks, which entered in a later year (late joiners hereafter). Indeed, banks become primary dealers on continuous basis and not only when the primary dealership is adopted for the first time[16]. The two groups will be used as treated and control units in the difference-in-difference section[17]. Table 2 compares selected variables between the two groups. Early joiners are compared against late joiners. For the latter group, only observations for years when they are not primary dealers are kept. For the sample

[15] I use as reference the list of variables used in Adelino and Ferreira (2016).

[16] USA, UK and Singapore review the status of their primary dealers every 6 months making sure that there is an appropriate turnover if some dealers are not compliant anymore.

[17] This is an alternative approach. The original setup considered credit ratings as basis for identification of treated and control groups.

of this research, we observe that that treated banks are on average 79% larger, 1% less solvent and 2% more liquid than control banks. The differences may be attributable to the status of primary dealer experienced by the treated group but many other variables are at stake. The difference-in-difference model will help to make safer conclusions.

Table 2

Summary Statistics of Primary Dealers

This table presents summary statistics of 147 primary dealers, divided into two groups: a) 90 banks, which entered into the system in the introduction year and 58 banks, which entered in a later year. Each group presents summary statistics for selected variables. The sample contains observations from 1988 to 2015 for 19 countries. The last column reports the difference mean of each variable with respect to the two groups of banks. *, **, *** indicates significant values of mean difference respectively at 10%, 5% and 1% according to the unequal variance robust t-statistic[18].

Variables	**Treated Group**			**Control Group**			**Mean difference**	
	Obs.	Mean	St. Dev.	Obs.	Mean	St. Dev.	Obs.	Diff.
Log of Total Asset ($ billion)	1,365	9.41	2.71	465	8.61	2.5	1,830	0.79***
Profitability (scaled by total assets)	1,274	1.15	4.46	406	0.89	2.53	1,680	0.25
Solvency	1,365	0.08	0.09	462	0.09	0.12	1,827	-0.01**
Retail Deposit	1,336	0.66	0.23	446	0.62	0.24	1,782	0.03**
GDP Growth	1,202	0.05	0.16	379	0.03	0.17	1,591	0.01*
Liquidity	1,365	0.3	0.19	465	0.28	0.2	1,830	0.02**
Loan To Deposit	1,330	1.09	1.15	443	1.56	3.83	1,774	-0.47***
Growth of Total Assets	1,269	21.73	54.52	406	29.03	70.77	1,675	-7.30**
(log change)	1,364	0.03	0.03	465	-0.09	0.06	1,829	0.12*
Growth of Loans	1,254	24.76	74.44	390	27.42	58.54	1,644	-2.66
(log change)	1,337	0.04	0.03	441	-0.05	0.06	1,778	0.08*
Number of Banks		90			58			

[18] Ruxton (2006) explains that the standard Student t-test is not reliable when variances differ between the underlying populations. This is especially the case when analyzing small samples since the t-distribution is normally distributed only for large sample sizes.

4 Event Study

4.1 Event Study Methodology

Event studies are one of the most used analytical tools in financial research[19]. The modern event study methodology is based on Fama et al., (1969).

Event studies are useful to determine the market's reaction to specific event. The basic idea is that new information brought by the event leads to changes in securities' stock price. However, stock prices change even without news, making difficult to recognise the reason of the change. Therefore, it is fundamental to distinguish the "normal" returns from the returns induced by the event under analysis. (Mackinlay, 1997). The abnormal return is the return caused by the event corrected by the "normal" one. It is common practice to predict the "normal" return for each stock using a regression.

The event study in this research examines the effects on the daily stock prices[20] of the banks when they become primary dealers. I study the effect over different periods of time before and after the announcement of the primary dealership for different countries. Some banks join the system only in a second moment, after the introduction of the system. The core part of this section is to establish whether the abnormal return persists over time and then create real value for the shareholders or it is just a temporary speculation.

The event dates are chosen as much precisely as possible to increase the quality of the analysis and are collected only from official sources. [21]

The event window is the horizon over which I detect the abnormal return, if any. I decide to include few days before the event since leakage of information may happen[22]. Indeed, the process of becoming a primary dealer or the procedure undertook by the government to establish the system takes a long time. It is likely that the news circulates before the official announcement. It must be said that the longer the event window, the higher the probability of including the noise of other unrelated events. Therefore, in section 4.2, I will present different event windows and discuss them.

[19] James Dolley (1933) introduced for the first time the event study methodology in financial research. He studied the returns effect of stock splits.

[20] As demonstrated by Bessembinder et al., (2006), the daily frequency is the best for event studies since it increases the power of the test statistics.

[21] Brown and Warner (1985) show the importance of choosing accurately the event dates to obtain reliable results. In most of the cases I retrieve event dates from official bulletin of central banks or ministry of finance. In few cases I use the first announcement in financial press.

[22] Glascock (1987) highlights the importance of considering leakage of information.

4.1.1 Market Model Method

The "normal" return is estimated over the estimation period, when no event takes place, using the market model. I set the estimation period to approximately one year if considering only trading days, starting 250 days before the event and ending 50 days before it. The event study covers 11 different countries[23] so I use the main market index of each country as proxy for market portfolio in the market model. DataStream provides an embedded function which automatically matches each stock with the most representative index of the country. The "normal" return for stock *j* at time *t* is estimated using an OLS regression[24] over the estimation window:

$$R_{j,t} = \alpha_j + \beta_j R_{m,t} + \varepsilon_j$$

where α is the average return of bank *j* not explained by the market, β is the sensitivity of bank *j* to the market index and ε is the error term. I account for autocorrelation and heteroscedasticity issues when discussing test statistics in the next sub-section since it is likely that the standard errors of the estimates are affected. The estimated "normal" return for stock *j* at time *t* is:

$$\hat{R}_{j,t} = \hat{\alpha}_j + \widehat{\beta}_j R_{m,t}$$

The abnormal return is the difference between the actual return and the predicted one:

$$AR_{j,t} = R_{j,t} - \hat{R}_{j,t} = R_{j,t} - (\hat{\alpha}_j + \widehat{\beta}_j R_{m,t})$$

I use the market model since it is the most appropriate statistical model in case of event-date clustering (Brown and Warner, 1985). In my dataset, many banks enter the primary dealership in the same day, potentially leading to cross-sectional correlation of abnormal returns, and distortions from event-induced volatility changes. This issue will be discussed again in this section when presenting test statistics.

To perform these last steps, I use Datastream Event Study Tool. It is an excel macro provided by Thomson Reuters which download stock prices from Datastream and compute the market model adjusted returns. The tool is based on Mackinlay (1997).

Since this is a cross-sectional study, I have to average the abnormal returns across banks. Therefore, during one day within the event window, the average abnormal return (AAR) across the banks in the sample is given by:

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[23] The sample covers 19 countries but missing stock price data reduce the coverage to 11 countries. See section 3.1 for more details.

[24] Brown and Warner (1985) show that OLS regression works as well as other more complex regressions.

$$AAR_t = \frac{1}{N\sum_{j=1}^{n} AR_{j,t}}$$

The cumulative average abnormal return (CAAR) is defined as the average across banks over the event windows of T days, where T=T2-T1.

$$CAAR_{T1,T2} = \sum_{t=T1}^{T2} AAR_t$$

4.1.2 Significance Tests

I need to test whether the abnormal returns computed using Datastream Event Study Tool are significantly different from zero. In the literature, we can distinguish between parametric and non-parametric test statistics.

I use the parametric crude dependence adjustment t-test (CDA t-test) and the non-parametric Corrado rank test. A mathematical description of both tests can be found in Appendix C.

The CDA t-test assumes normally distributed abnormal return and was introduced by Brown and Warner (1985) as an attempt to correct for issues like heteroscedasticity and cross-sectional dependence. The dataset of the research is likely to suffer from both cross-sectional correlation and event-induced volatility since many companies experience the event in the same day (event-date clustering). If the dataset is affected by the last two issues it is likely that the standard deviation of abnormal return is underestimated and the t-statistic overstated, detecting too often significant abnormal return Therefore, it is important to correct for the potential dependence of returns across security-events.

The procedure suggested by Brown and Warner (1985) implies that the variance of the returns over the event window is computed using the average performance measures in the estimation period meaning that any cross-sectional dependence is taken into account.

The non-parametric Corrado (1989) and Corrado and Zyvney (1992) rank test, updated according to Campell and Wasley (1993), accounts for cross-sectional correlation and event-induced volatility as well. Additionally, being a non-parametric significance test, it does not require normally distributed abnormal returns for individual companies. Since it is well known that daily return distributions are far to be normally distributed[25], it is common practice among scholars to use both parametric and non-parametric tests when conducting an event study in order to provide also a test, which is robust, for instance, to outliers (Schipper and Smith, 1983). I put emphasis on the non-parametric test for two reasons. Firstly, it is a robustness check,

[25] Fama (1976, Ch. 1) shows that daily return distributions are fat-tailed, exhibiting different skewness and kurtosis than the normal distribution.

which is conducted in many papers, and secondly non-normality and outliers may play a role due to the small size of the dataset. Autocorrelation should not pose an issue since the event period is short relative to the estimation period (Binder, 1998).

4.2 Event Study Results

Table 3 presents some statistic properties of the cross-section returns for the 66 banks. I use different measures of performances following Brown and Warner, (1985).

Table 3

Cross-sectional properties of Alternative Performance Measures at day '0'

This table reports the average of different performance measures for the sample of 66 banks at day '0'. *, **, *** indicate that the mean is statistically different from zero respectively at 10%, 5%, 1% according to the t-statistic. Skweness and kurtosis measure respectively the symmetry and peakedness of return distribution. The Shapiro-wilk test indicates the extent to which returns are normally distributed.

Performance Measure	Mean	SD	Skweness	Kurtosis	Shapiro-Wilk Test (Prob>Z)
Raw Returns	-0.0025	0.0136	-0.4146	3.7998	0.00042
Market Model	-0.0003	0.0119	0.5799	7.2731	0.00001
Mean Adjusted	-0.0025	0.0136	-0.4146	3.7998	0.00042

The average returns under all three performance measures are not significantly different from zero. This is not surprising since I am analysing only day '0' following the example in Brown and Warner (1985). The Shapiro-Wilk test for normality[26] reveals that returns are not normally distributed under all the cases, confirming the tendency of daily excess returns to depart from normality (Fama, 1976). Market model returns exhibit a higher kurtosis with respect to the other measures implying a more peaked distribution than the normal one[27]. This means that the distribution of this returns has "fat tails" and the probability of extreme outcomes is higher than in the other cases. Moreover, the market model is the only performance measure to show positive skewness with the positive area of the distribution being more pronounced than the negative one. The non-normality of returns supports the use of non-parametric significance test.

[26] The null-hypothesis of the Shapiro-Wilk test is that data are normally distributed.
[27] A distribution with kurtosis larger than three is called leptokurtic.

Table 4

Cumulative Abnormal Primary Dealers' Return

This table presents cumulative abnormal return around the announcement of the inclusion into the primary dealerships of 66 international banks. The numbers in the table are the mean or median of the cumulative abnormal returns over different event windows. *, **, *** indicates significant values of mean or median respectively at 10%, 5% and 1% according to the t-statistic.

Window	CDA T-test		Rank T-test	
	Mean	Median	Mean	Median
[-30,-1]	1.38%	0.42%	1.38%	0.42%
[-5,-1]	0.62%	0.22%	0.62%	0.22%
[0,+1]	0.44% *	0.20%	0.44%	0.20%
[0,+5]	0.64%	0.38%	0.64%	0.38%
[0,+15]	2.80% ***	1.73% *	2.80% *	1.73% *
[0,+30]	2.86% **	1.72%	2.86%	1.72%

As shown in left portion of table 4, both the mean and median of the cumulative abnormal returns are not significantly different from zero over the days before the event [-5, -1] and [-31,-1] when using a CDA t-test. I decided to analyse these event windows because sometimes the news is leaked, especially in this case, when the procedure to become primary dealer takes a long time and media or institutional investors may become aware well before the news is officially published.

On the other hand, the mean is statistically significant for three different windows starting on day-0 and ending on days +1, +15 and +30 while the median is significant only over the event window (0, +15). Over this last event window, the mean of cumulative abnormal return is 2.80% and median is 1.73%.

Since the return distribution is positively skewed, it is fundamental to consider the median as a superior measure of central tendency[28]. Indeed, it is likely that the average of returns is influenced and dragged towards the direction of the skew.

In the right portion of table 4 the significance of cumulative abnormal returns is tested using the non-parametric Corrado rank test. As discussed in the methodology section this is an

[28] Also called measure of central location since it is a statistical measure, which identifies the central position within a set of data.

important robustness check for the reliability of the results. When using the rank t-statistic, the point estimates of the mean and median CARs during the fifteen-day window from 0 to +15 are significantly different from zero at the 10%. A cumulative average (median) abnormal return of 2.80% (1.73%) over 15 days is substantial.

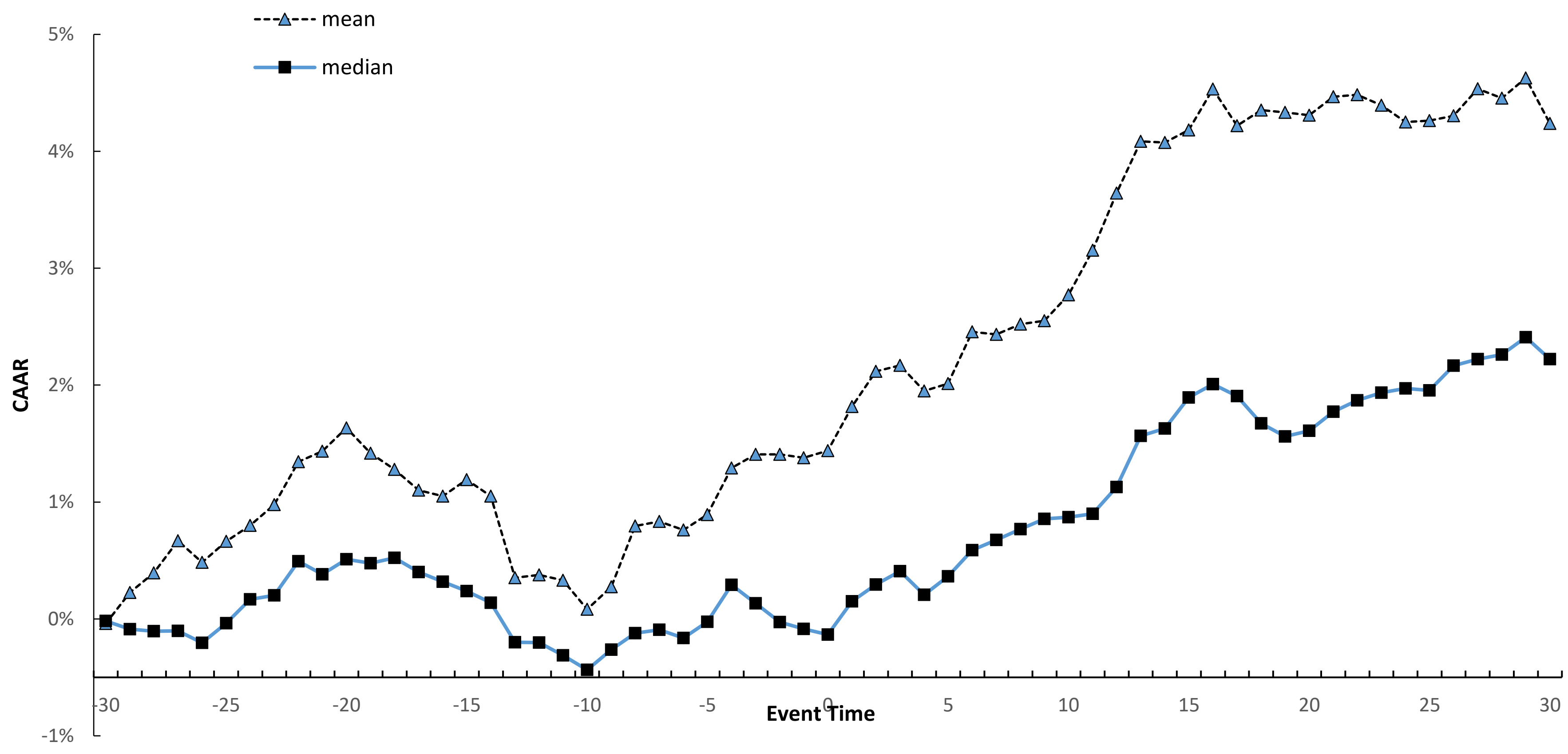
The analysis leads to the conclusion that new appointed primary dealers become attractive to investors. They perceive the news as positive, bidding up the stock price of the recently appointed dealers. However, the reaction is not immediate and it takes some days to incorporate the information. Investors slowly react to new information. Some of the banks in the sample are small stock since they are separately listed from the parent bank. This evidence may reconcile with the results presented by Chan (2003) that investors react slowly to small stocks related news. Table 15 in Appendix C provides further details, including additional event windows.

Figure 1 shows how the mean and median CARs do not revert to normality over the weeks after the event. This means that, over the 30 days window after the event, the CARs are persistent, generating real and long-term value for primary dealers' shareholders. Mean CARs react more sharply in the days after the event than median CARs. Focusing on the median measure, before the event day (day '0') and over the window (-30, 0), the CARs do not show a clear pattern and from the graph it is unambiguous that it fluctuates around the median of approximately 0. After the day '0' the graph clearly shows the impact of the event. Both mean and median CARs progressively rise, confirming that the market slowly learns about the event and reaching a peak around day-15 of the event window. After day-15 the cumulative abnormal return remains stable up to day-30.

Figure 1

Average Abnormal Cumulative Returns over Time

Plot of cumulative average abnormal returns from event day -30 to event day 30. The event date (day '0') corresponds to the entrance of the 66 banks into the primary dealership. The abnormal return is calculated using the market model as the normal return measure.



5 Difference-in-Difference Model

The difference-in-difference (DiD) technique aims to detect causal effects and is a well-established econometric tool[29]. It is based on the comparison of pre- to post-intervention outcomes for two separated but almost identical groups of subjects. One group (treated) is exposed to the treatment over one period and no treatment over the second period. The other group (control) is not exposed to the treatment over both periods. Therefore, the differences between the two identical groups should entirely derive from the exposure to the treatment since any other common effects to both group is accounted for. In general, DiD allows to test the effect of a treatment (Ti) on an outcome (Yi). One of the main assumptions of the DiD approach is the parallelism between the two groups: in absence of the treatment both control and treated group should present the same changes over time.

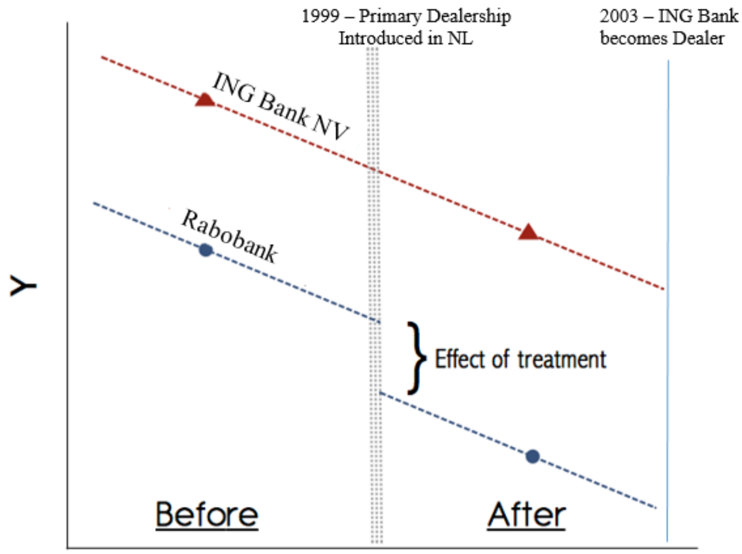
5.1 Defining Treated and Control Groups

I distinguish between dealers, which entered into the dealership in the introduction year (treated group) and those, which entered only in a later moment (control group). The former group acquires benefits due to the inclusion in the new system[30] while the latter should not experience any effect around dealerships introduction dates. For the control group, I make sure that the time-series observations end at the point in time they become dealers. These two groups have very similar characteristics, as already discussed in section 3, since the banks are all potential primary dealers and they all join the system at some point in time. Therefore, the parallel trend assumption should hold. Figure 2 depicts the logic behind this analysis for a single treated and control bank. Primary dealership is introduced in the Netherlands in 1999 and Rabobank (treated unit) is one of the banks that joins the system in the early stage while ING Bank (control unit) joins 4 years later, in 2003. No observations are kept after 2003 since ING Bank itself would experience the benefits of the primary dealer.

[29] Snow (1854) was the first to introduce difference-in-difference in scientific research.
[30] See section 1 for a detailed explanation of the privileges of primary dealers.

Figure 2

Difference in Difference estimation, graphical explanation



5.2 The Model and Variables

This part of the analysis focuses on detecting changes in selected variables, which proxy for balance sheet expansion in securities and liquidity, for both the treated and control group.

I am analyzing multiple entrances into primary dealerships for different countries at a variety of times. Following Hansen (2007a) and Bertrand et al., (2004) a fixed-effects estimation of panel data is conducted. The regression model is given by:

$$(1)\quad Y_{i,t} = \beta_o + \beta_1 T_i A_t + u_i + \mu_t + \varepsilon_{i,t} + C_{i,t}$$

$$(2)\quad Y_{i,t} = \beta_o + \beta_1 T_i + \beta_2 A_t + \beta_3 T_i A_t + \varepsilon_{i,t} + C_{i,t}$$

where u_i is the bank fixed-effects, μ_t is a complete set of year (time) effects and $T_i A_t$ are two dummy variables which capture the effect on treated banks ($T_i = 1$) after they enter into the primary dealership ($A_t = 1$). In model (1), the coefficient of interest, the difference-in-difference estimator, is β_1 and it captures the net effect on primary dealers. Model (2) excludes fixed effects. A_t and T_i are not reported in model (1) because they would be collinear respectively with the time and bank fixed effects. In model (2) β_1 is the estimated mean difference in Y in treated and control groups prior to the intervention. β_2 is the expected mean change in Y before and after the intervention for the control group. Coefficient β_3 , in both models, is the expected mean change in Y from before to after the intervention in the two groups. The sum of β_1 *and* β_2 in model (2) is the estimated mean difference in Y between the two groups after the intervention.

The model includes bank-level fixed effects to control for time-invariant variables that have not been measured but affect the outcome Y. This method allows correcting for omitted variables bias.

Moreover, since many variables can be correlated with the outcome Y and, more importantly, they are likely to be time-variant, control variables are added to the regression ($C_{i,t}$). These covariates should not be outcome themselves of the treatment. The literature mentions two main reasons to include control variables in a difference in difference model: a) the parallel trend between treated and control groups is likely not to be perfect and then additional covariates will increase the precision of the difference-in-difference estimates; b) the reduction of the error variance, and then increase the power of statistical tests. Therefore, I will present results including and excluding control variables to assess any difference brought by their addition.

Potential multi-collinearity issue is automatically corrected in Stata. I use robust standard errors to correct for heteroscedasticity and autocorrelation issues.

To detect balance sheet expansion, I use as dependent variable *Growth of Total Assets*. To detect liquidity changes I use the following funding variables: *Retail Deposits, Non-Deposits Short-Term Funding, Interbank Funding, and Long-Term Funding* as defined in Adelino and Ferreira (2016).

I use the following bank characteristics as control variables: *Size, Profitability, Solvency, Liquidity, and Deposits.* The selection of control variables is also based on Adelino and Ferreira (2016). Variables definition is provided in appendix E.

As mentioned in Panayiotis et al. (2005), Sudin (1996) and Valentina et al. (2009), larger banks are usually more profitable due to economies of scale, higher expertise level and larger number of clients. When banks increase liquid holdings, they do so at the opportunity cost of some investments, which could generate higher return: liquid assets have lower yield than other categories of assets (e.g. loans). Therefore, the expected relation between funding variables and profitability is negative while the expected relation between *Growth of Total Assets* and *profitability* is positive. Moreover, I expect the magnitude of customer deposit, to be positively correlated with asset growth.

Capital ratios affect liquidity. The direction of this relation is a matter of discussion in the outstanding literature. Diamond and Rajan (2001) argue that higher capital allows banks to engage in riskier activities shifting their focus towards higher yield investments than liquid assets. Another strand of literature (e.g. Allen and Gale, 2004) argues that liquidity creation exposes banks to risk. The larger the liquid holdings, the higher the probability of losses due to disposal of illiquid assets to meet the liquidity demands of customers.

5.3 Difference-in-Difference Model Results

The tables in this section present the results relative to the difference-in-difference model and for 5 different outcome variables, defined in the previous section. Each table is accompanied by a graph presenting the base specification augmented with lead and lags for both treated and control groups. Appendix F reports graphs depicting the year-by-year outcome variables for treated and control groups.

Regression (1) in table 5 shows that treated and control groups have similar estimated means of *Growth of Total Assets* in the pre-treatment period: the baseline difference β_1 is not significant and the left portion of Figure 3 clearly shows a parallel trend between treated and control groups for the above-mentioned Y outcome. The estimated mean change in *Growth of Total Assets* for the control group before and after the treatment (β_2) is negative and significant, meaning that the mere effect of passage of time has a detrimental impact on balance sheet growth rate of control banks: the expected mean change in *Growth of Total Assets* from before to after, among the control group, is about -13%. In the post-treatment period, the impact on *Growth of Total Assets* for control banks is more negative than for treated units. Control banks experience a persistent and decreasingly more negative effect on *Growth of Total Assets* than treated units. In the year of entrance into the dealership (time ‘0’), *Growth of Total Asset* increases by approximately 12% for treated banks and decrease by 29% for control banks. Overall, the difference-in-difference estimate in regression (5), controlling for bank characteristics, time and firm fixed effect estimate, is positive and significant. The expected mean change in *Growth of Total Assets* from before to after is different in the two groups: treated banks show a 10.5% higher *Growth of Total Asset* than control ones. The difference in difference estimate in regression (4) has a similar magnitude, meaning that the inclusion of bank characteristics as control variables has a trivial impact. As expected, *Profitability* control variable is positively and significantly correlated with growth of banks’ balance sheets: a 1% increase in *Profitability* ratio has a 6% positive impact on the *Growth of Total Assets,* everything else being fixed. Moreover, I find evidence that *Growth of Total Assets* is significantly and negatively related to *Solvency* ratio: a 1% increase in *Solvency* ratio brings an approximate decrease in *Growth of Total Assets* of 2.4%. The more solvent a bank is, the more negative its balance sheet growth.

Table 5

Growth of Total Assets: Difference-in-Difference Estimates

The table shows the impact of becoming a primary dealer on growth rate of total assets. Difference-in-difference estimates are reported along with control variables coefficients. Different specifications of the model are presented in order to include fixed effects and control variables. *, **, *** indicates significant values of the coefficients respectively at 10%, 5% and 1% according to the t-statistic. Robust standard errors are reported in parenthesis.

Variables	**Growth of Total Assets**				
	(1)	(2)	(3)	(4)	(5)
Diff-in-Diff	-6.47	-11.49***	6.71	10.63**	10.51**
	(8.67)	(3.77)	(10.77)	(5.38)	(5.15)
Size					-2.53
					(5.31)
Profitability					6.09***
					(1.19)
Solvency					-2.37***
					(0.54)
Deposit					-45.32
					(31.68)
Liquidity					8.93
					(28.13)
After	-12.61*		-26.33***		
	(7.81)		(10.14)		
Treated	-4.75	1.12			
	(7.77)	(5.18)			
Constant	36.15***	21.78	34.35***	32.00***	69.39
	(6.98)	(19.15)	(1.86)	(5.33)	(45.02)
Observations	1,675	1,675	1,675	1,675	1,663
R-squared	0.02	0.05	0.02	0.02	0.09
Bank FE	NO	NO	YES	YES	YES
Year FE	NO	YES	NO	YES	YES

Figure 3

Estimated impact of becoming primary dealer on Growth of Total Assets for years before, during, and after entering the primary dealership.

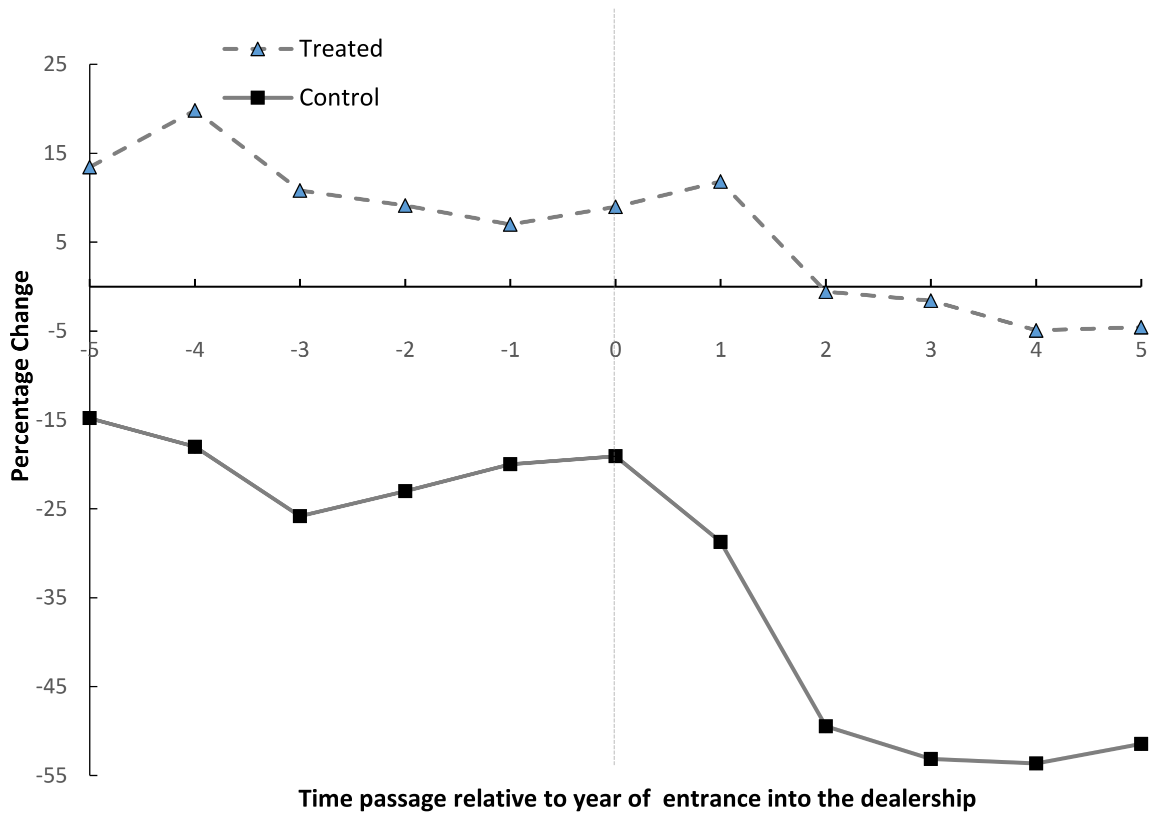


Table 6 presents the difference-in-difference regressions for *Retail Deposits* outcome variable. As depicted in figure 4, treated and control banks follow a common pattern in the pre-treatment period. β_1 coefficient in regression (1) is not significant confirming that estimated means of *Retail Deposit* are not different between treated and control group. The estimated mean change in *Retail Deposits* for the control group before and after the treatment (β_2) is negative and significant, meaning that the pure effect of passage of time has a negative impact on retail deposits size: the expected mean change in *Retail Deposits* from before to after among the control group is -8%. In the post-treatment period, the two groups exhibit opposite trends: the impact of treated banks on Y outcome fluctuates between 1% to 4%, implying a growing absolute effect on the *Retail Deposits* while the impact of control banks is increasingly negative during the first three years of the post-treatment period.

Overall, the expected mean change in *Retail Deposits* from before to after the treatment (diff-in-diff coefficient in regression 4) is significantly different between the two groups and equal to 4%. The inclusion of control variables does not significantly change the result. This result may reconcile with the one of the concepts explained in section 1. Becoming a primary dealer has a positive effect on the reputation and reliability of the bank. This important recognition is used for purposes by the bank to enlarge their customer base.

Table 6

Retail Deposits: Difference-in-Difference Estimates

The table shows the impact of becoming a primary dealer on retail deposits. Difference-in-difference estimates are reported along with control variables coefficients. Different specifications of the model are presented in order to include fixed effects and control variables. *, **, *** indicates significant values of the coefficients respectively at 10%, 5% and 1% according to the t-statistic. Robust standard errors are reported in parenthesis

Variables	**Retail Deposits**				
	(1)	(2)	(3)	(4)	(5)
Diff-in-Diff	0.07***	0.02	0.06**	0.03*	0.04**
	(0.03)	(0.02)	(0.03)	(0.02)	(0.02)
Size					-0.02
					(0.02)
Profitability					0.00
					(0.00)
Solvency					0.60***
					(0.11)
Deposit					0.28***
					(0.11)
Liquidity					0.02
					(0.08)
After	-0.08***		-0.07***		
	(0.02)		(0.19)		
Treated	-0.02	0.02			
	(0.04)	(0.04)			
Constant	0.66***	0.54***	0.66***	0.55***	0.39**
	(0.03)	(0.08)	(0.01)	(0.05)	(0.16)
Observations	1,782	1,782	1,782	1,782	1,640
R-squared	0.01	0.01	0.02	0.01	0.08
Bank FE	NO	NO	YES	YES	YES
Year FE	NO	YES	NO	YES	YES

Figure 4

Estimated impact of becoming primary dealer on *Retail Deposits* for years before, during, and after entering the primary dealership. Estimates are reported for both treated and control units.

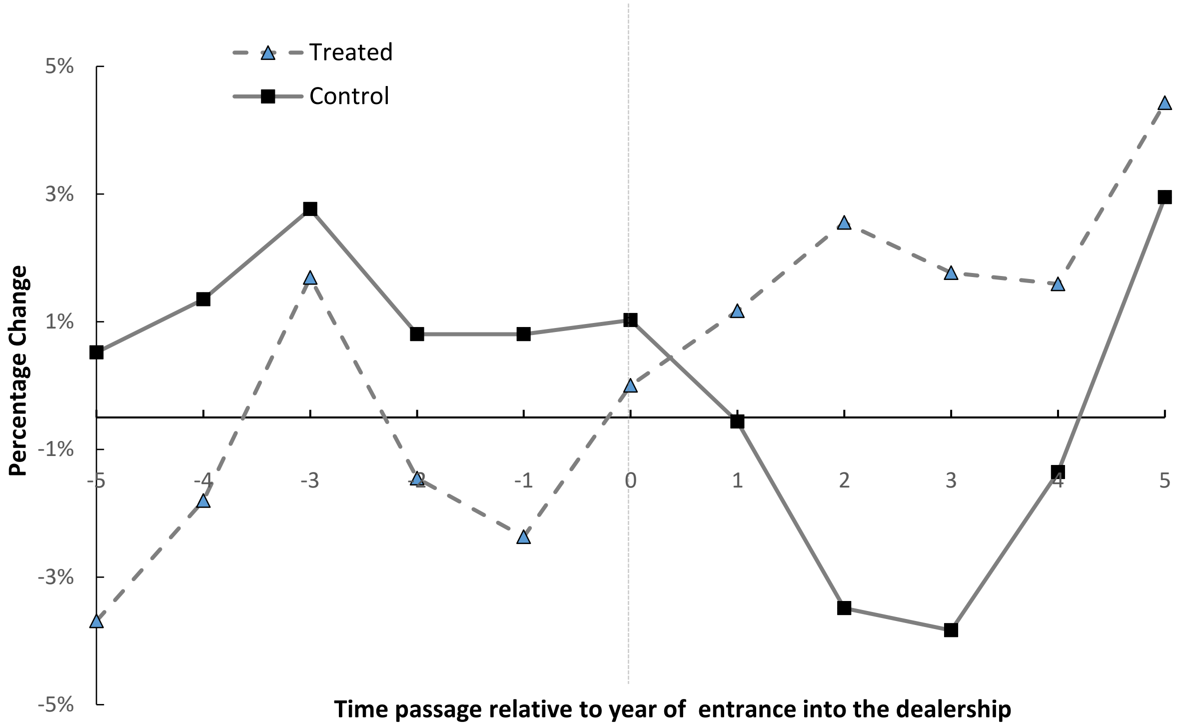


Table 7 presents the difference-in-difference regressions for *Non-Deposits Short-Term Funding* outcome variable. Figure 5 shows that treated and control banks follow a common pattern in the pre-treatment period. The coefficient β_1 in regression (1) is not significant confirming that estimated means of the outcome variable are not different between treated and control group in the pre-treatment period. Similarly, in the post-treatment period the two groups exhibit similar impacts on the outcome variable. This is also evident in the right portion of figure 5 and confirmed by the non-significant difference-in-difference coefficients in regressions (4) and (5). Therefore, the expected mean change in *Non-Deposits Short-Term Funding* from before to after the treatment is not significantly different between the two groups. *Size* and *Deposits* are both positively correlated with the outcome variable. The bigger the banks, the larger the *Non-Deposits Short-Term Funding* ratio. It may be the case that big banks have easier access to wholesale funding than small banks: an increase of 1% in bank *Size* brings an increase of 3% in *Non-Deposits Short-Term Funding*. The positive relation between *Deposits* and the outcome variable is mainly driven by the way *Deposits* is defined. See Appendix E for variable description.

Table 7

Non-Deposits Short-Term Funding: Difference-in-Difference Estimates

The table shows the impact of becoming a primary dealer on non-deposits short term funds. Difference-in-difference estimates are reported along with control variables coefficients. Different specifications of the model are presented in order to include fixed effects and control variables. *, **, *** indicates significant values of the coefficients respectively at 10%, 5% and 1% according to the t-statistic. Robust standard errors are reported in parenthesis.

Variables	**Non-Deposits Short-Term Funding**				
	(1)	(2)	(3)	(4)	(5)
Diff-in-Diff	-0.06**	-0.02	-0.06**	-0.03	-0.03
	(0.03)	(0.02)	(0.03)	(0.02)	(0.02)
Size					0.03*
					(0.02)
Profitability					0.00
					0.00
Solvency					-0.05
					(0.12)
Deposit					0.39***
					(0.09)
Liquidity					-0.03
					(0.06)
After	0.03		0.03		
	(0.20)		(0.21)		
Treated	-0.01	-0.03			
	(0.04)	(0.04)			
Constant	0.29***	0.44***	0.28***	0.43***	-0.04
	(0.03)	(0.07)	(0.01)	(0.04)	(0.16)
Observations	1,782	1,782	1,782	1,782	1,640
R-squared	0.01	0.03	0.01	0.02	0.01
Bank FE	NO	NO	YES	YES	YES
Year FE	NO	YES	NO	YES	YES

Figure 5

Estimated impact of becoming primary dealer on *Non-Deposits Short-Term Funding* for years before, during, and after entering the primary dealership. Estimates are reported for both treated and control units.

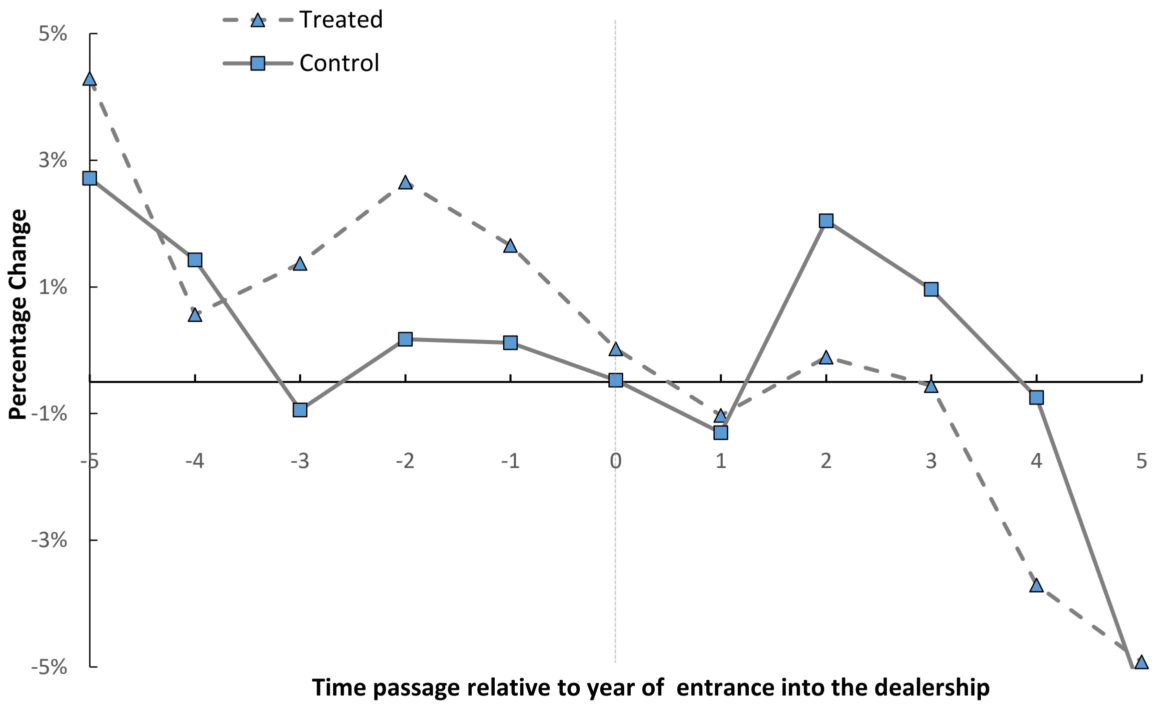


Table 8 presents the difference-in-difference regressions for *Interbank Funding Ratio* outcome variable. Figure 6 shows that treated and control banks follow a common pattern in the pre-treatment period. The coefficient β_1 in regression (1) is not significant confirming that estimated means of the outcome variable are not different between treated and control group in the pre-treatment period. In the post-treatment period, the treated units show a negative impact on the outcome variable while control units ‘impact is fluctuating.

The estimated mean change in *Interbank Ratio* for the control group before and after the treatment (β_2) is negative and significant at 10% confidence interval, meaning that the pure effect of passage of time has a negative impact on the outcome variable: the expected mean change in *Interbank Ratio* from before to after among the control group is about 30%. Despite this decrease in absence of actual intervention, the expected mean change in *Interbank Ratio* from before to after the treatment is not significantly different between the two groups. Difference-in-difference coefficient in regression (4) and (5) is positive but not significant.

Deposit control variable is negative related to the outcome variable: the larger the exposure of the bank to the money market for funding, the lower the need for deposits. An increase of 1% in *Deposit* ratio brings a decrease of almost 20% in *Interbank Funding.* The positive relation between *Liquidity* ratio and the outcome variable is straightforward: the interbank market is by definition liquid.

Table 8

Interbank Funding: Difference-in-Difference Estimates

The table shows the impact of becoming a primary dealer on interbank funding. Difference-in-difference estimates are reported along with control variables coefficients. Different specifications of the model are presented in order to include fixed effects and control variables. *, **, *** indicates significant values of the coefficients respectively at 10%, 5% and 1% according to the t-statistic. Robust standard errors are reported in parenthesis.

Variables	**Interbank Funding**				
	(1)	(2)	(3)	(4)	(5)
Diff-in-Diff	16.12	-11.20	25.05	22.98	29.01
	(25.35)	(21.22)	(25.95)	(22.67)	(21.18)
Size					-4.73
					(18.92)
Profitability					-1.90
					(1.74)
Solvency					60.92
					(187.72)
Deposit					-20.40**
					(11.67)
Liquidity					47.24***
					(7.61)
After	-29.12*		-37.94*		
	(17.06)		(17.51)		
Treated	25.72	41.83*			
	(26.02)	(23.02)			
Constant	148.36***	49.13**	161.98***	102.39***	152.79
	(19.80)	(28.62)	(7.26)	(29.42)	(200.460)
Observations	1,588	1,588	1,588	1,588	1,470
R-squared	0.01	0.03	0.01	0.01	0.09
Bank FE	NO	NO	YES	YES	YES
Year FE	NO	YES	NO	YES	YES

Figure 6

Estimated impact of becoming primary dealer on *Interbank Ratio* for years before, during, and after entering the primary dealership. Estimates are reported for both treated and control units.

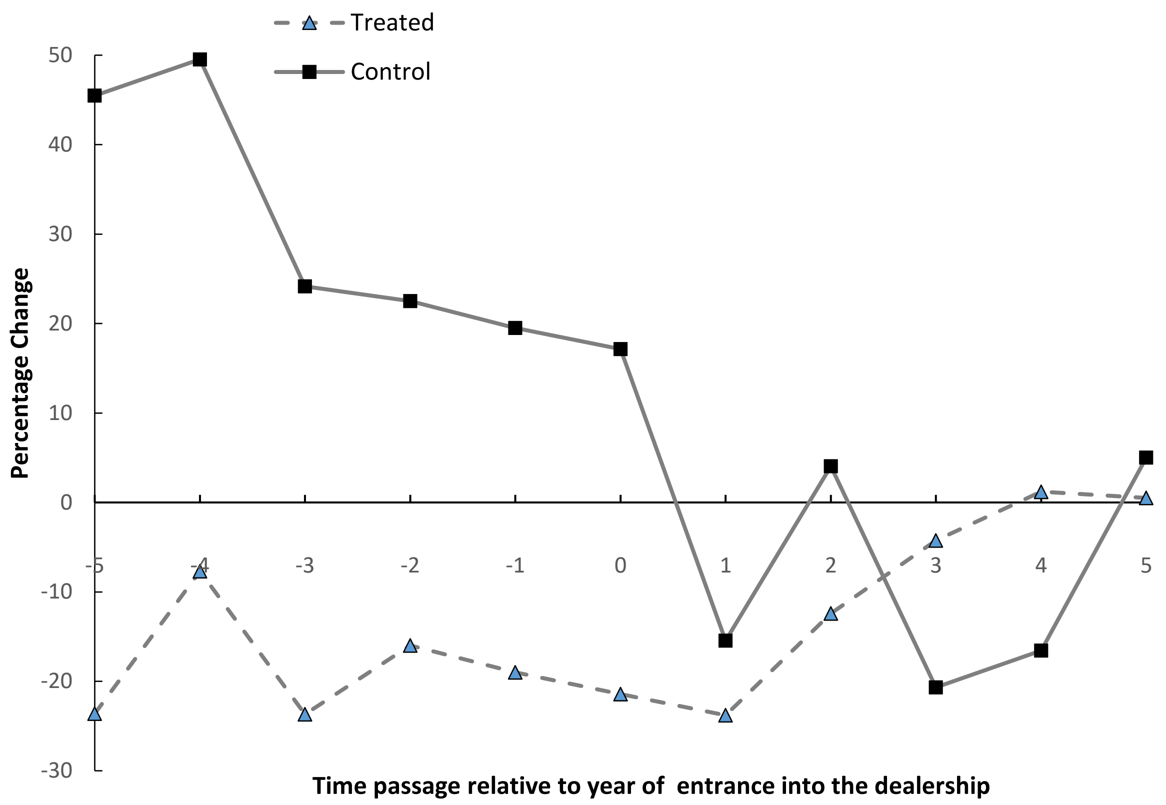


Table 9 presents the difference-in-difference regressions for *Long-Term Funding* outcome variable. Figure 7 shows that, in the post-treatment period, the control units have a positive and increasing impact on the outcome variable implying a growing absolute effect on *Long-Term Funding.* This is unexpected since treated units and not control ones should exhibit such treatment according to the theoretical framework of the research.

The estimated mean change in *Long-term Funding* for the control group before and after the treatment (β_2) is positive and significant at 1% confidence interval, meaning that the pure effect of passage of time has a positive impact on the outcome variable: the expected mean change in *Long-term Funding* from before to after among the control group is about 5%.

Overall, the expected mean change in *Long-term Funding* from before to after the treatment (diff-in-diff coefficient in regression 4) is not significantly different between the two groups. The inclusion of control variables does not significantly change the result.

Table 9

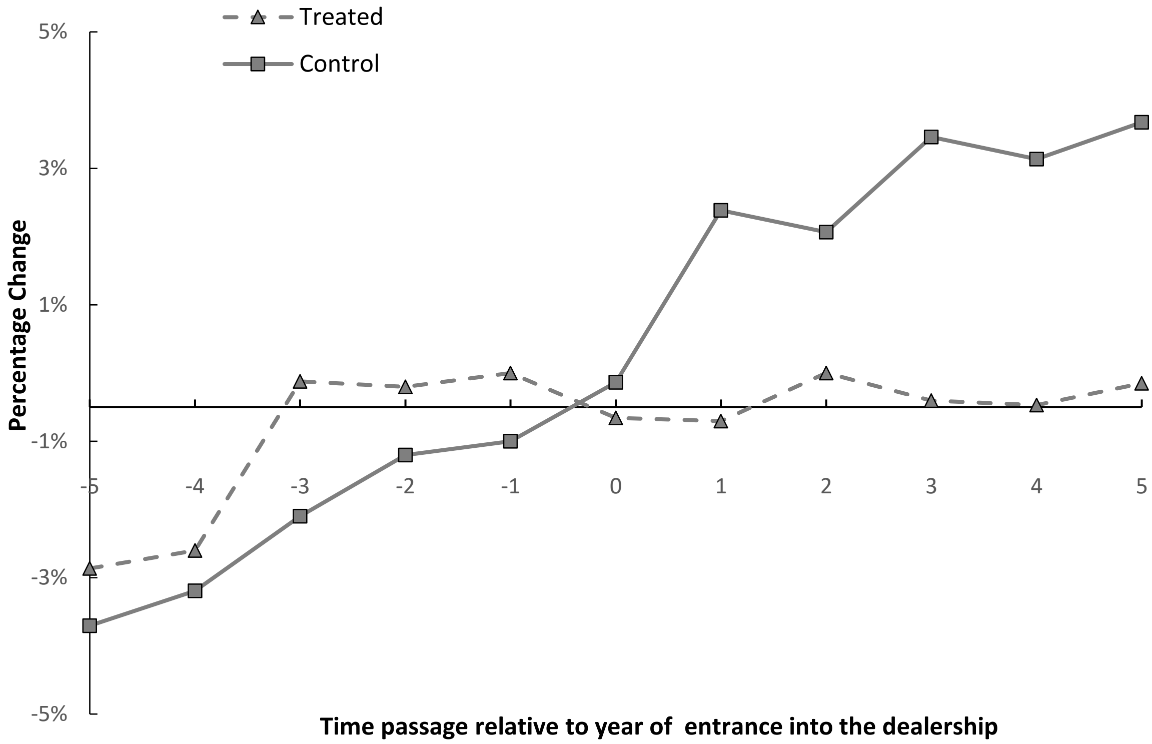
Long-Term Funding: Difference-in-Difference Estimates

The table shows the impact of becoming a primary dealer on long-term funding. Difference-in-differences estimates are reported along with control variables coefficients. Different specifications of the model are presented in order to include fixed effects and control variables. *, **, *** indicates significant values of the coefficients respectively at 10%, 5% and 1% according to the t-statistic. Robust standard errors are reported in parenthesis.

Variables	**Long-Term Funding**				
	(1)	(2)	(3)	(4)	(5)
Diff-in-Diff	-0.02	0.005	-0.02	-0.03	-0.03
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Size					0.00
					(0.01)
Profitability					-0.001***
					(0.00)
Solvency					-0.46***
					(0.10)
Deposit					-0.57***
					(0.09)
Liquidity					-0.06***
					(0.02)
After	0.05***	-0.02	0.05***		
	(0.01)	(0.02)	(0.01)		
Treated	0.01				
	(0.02)				
Constant	0.05***	0.04**	0.06***	0.03**	0.55***
	(0.02)	(0.02)	(0.00)	(0.01)	(0.08)
Observations	1,700	1,700	1,700	1,700	1,560
R-squared	0.02	0.02	0.02	0.02	0.59
Bank FE	NO	NO	YES	YES	YES
Year FE	NO	YES	NO	YES	YES

Figure 7

Estimated impact of becoming primary dealer on *Long-term Funding for* years before, during, and after entering the primary dealership. Estimates are reported for both treated and control units.



6 Limitations and Further Research

This research suffers from small sample size. Only 147 primary dealers have been identified along with the date they become primary dealers. Many of these banks are subsidiaries incorporated in a host country but owned by a foreign parent bank. They are small and sometimes private banks, limiting the availability of complete financial data. The only database, which provides financial historical data up to 15 years for both listed and private banks, is Bankscope. Unfortunately, as per 1st January 2017, Bankscope is no longer available and has been replaced by Orbis Bank database. The latter covers historical data up to 5 years for listed banks and up to 3-4 years for private banks. Future research on this topic will be impacted by the scarcity of historical financial data on banks, especially private ones.

Event Study

It would have been easier to conduct the event study using parent banks stock prices. Indeed, many subsidiaries are not listed or have been unlisted over time. The usage of parent banks data, would have increased the sample size and availability of historical share price data but, at the same time, reduced the accuracy of the outcome. It could have been difficult to identify the subsidiary impact on parents' stock price among many other global factors. As far as I am concerned, there is no outstanding literature conducting an event study on such a global dataset of primary dealers. Future research may focus on a larger dataset and on longer event windows to study whether the cumulative average abnormal returns are still persistent.

Credit Rating Model

The main reason to introduce a credit rating model is due to missing credit ratings for some of the primary dealers in the sample. This drawback is driven by the limited release of credit ratings for private banks. To the best of my knowledge, no previous study has analyzed credit ratings of primary dealers using such a global dataset and setup. Applying this model to a much larger set of primary dealers may be addressed by future research.

Difference-in-Difference

The small sample size affected the methodology of the difference-in-difference analysis. The ideal control group, made of banks with credit rating higher or equal than the respective sovereign rating, was too small with respect to the treated one. This made the comparison between the groups not reliable at all. The alternative solution adopted brought extra complications. Using as control group subjects, which become treated themselves at some point in time, significantly reduced the number of observations post treatments for this group. Even though the number of pre- and post-treatment observations does not need to be the same, this last characteristic may have an impact on the significance of results. Non-parallel trends of the groups is another aspect, which may have created issues. Future research may want to focus on an alternative selection of treated and control groups and a different mix of dependent variables.

7 Conclusions

Primary dealers play a fundamental role in markets for government securities strengthening the functions, operations and the development of primary and secondary markets for government securities. Dealers acquire some benefits, becoming an important counterparty of both the sovereign debt manager for profitable debt management operations and the national central bank for monetary policies. Financial markets positively value their role to such an extent that primary dealers experience a significant abnormal stock returns in the two weeks following the appointment to dealer. This is in line with initial expectation and hypothesis. Even though market players know well in advance about banks' appointment to primary dealer, they still positively react when those banks become effectively operational. The cumulative abnormal returns turn significant only over the two weeks after the appointment meaning that some investors are slow to react to information.

Primary dealers are usually top tier banks and associated with high credit ratings. However, some of them are subsidiaries of top tier foreign parent banks and operate in emerging countries. This means that they are exposed to the macroeconomic risk of the hosting country and may exhibit a credit rating, which is heavily influenced by the sovereign rating of this country where they operate. On the other hand, the subsidiary financial condition may also depend on the parent bank's country of origin sovereign rating. These two variables are included in the credit rating model, helping to explain the variation of primary dealer credit ratings in the cross-country dataset of this study.

Primary dealers help the government to transport liquidity into other markets. They buy government securities at auction and hold the securities in inventory until they find an acquirer in the secondary market. They absorb the imbalances of the transaction in their own balance sheets, carrying large securities inventory. The evidence from the difference-in-difference models reconciles with the expectation of dealers 'balance sheet expansion. Results shows that becoming a primary dealer brings higher growth in total assets compared to control banks. The findings about liquidity and funding variables are surprising. None of the funding variables employed points in the direction of more liquid primary dealers compared to control banks.

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APPENDIX A: Original Methodology and Credit Rating Model

This section describes the initial setup that I had in mind to conduct the difference-in-difference analysis describing a different identification strategy for treated and control group along with its drawbacks and reasons why an alternative approach has been used. Despite being a dead-end approach, it ultimately brings interesting insights regarding credit ratings of the primary dealers in the sample.

According to the sovereign ceiling policy, banks cannot be rated above the sovereign. The idea is that private companies cannot borrow on better terms than the government since sovereign default triggers private defaults. Despite this rule still dominates in the majority of cases, rating agencies have violated it in few cases and this anomalous practice is becoming more frequent than in the past[31]. What I expect to find is that only a small fraction of banks has a higher rating than the sovereign. If the majority of banks is rated below or equal to the sovereign, the hypothesis that banks buy advantages when becoming a dealer counterparty of the government would be confirmed.

It is important to make a distinction here. Banks with higher or equal rating than the sovereign (1) should exhibit lower impact from the inclusion into the primary dealership with respect to banks with lower rating than the sovereign (2). The latter banks buy a liquidity put since their condition is improved and the system gives them more stability and protection in case of financial distress or default. Banks (2) should experience lower riskiness of bonds, higher funding liquidity and lower funding costs. Therefore, banks (2) receive the treatment while banks (1) are untreated and potentially are a good control group to control for factors which may affect banks' characteristics but are unrelated to the mere effects of becoming a primary dealer. The selection of these two groups is made in order to study the differential impact of the treatment (entrance into the primary dealership) on each of them. Since primary dealers must comply with some entry requirements set by the national legislator, the banks in both groups should have similar characteristics and follow the parallel trend assumption; namely, the only substantial and observable difference between the two groups should be attributable to the treatment. Therefore, looking at the credit rating of a bank in the year when it becomes primary dealer is enough to allocate the bank to one of the two groups (i.e. treated or control).

[31] Adelino and Ferreira (2016); Borensztein, Cowan and Valenzuela (2013) support the sovereign ceiling policy.

Following Adelino and Ferreira (2015) I map both sovereign and banks credit ratings into 16 numerical categories where 16 is the highest rating (AAA), 15 the second highest (AA+), and one the lowest (B-). Appendix D reports the conversion of the long-term credit ratings from the three main agencies into numerical categories. I use the unsecured long-term issuer ratings provided by Bankscope.

A large portion of the dataset is composed of private and/or unrated subsidiaries banks complicating the retrieval process of credit ratings from Bankscope. The database is incomplete and does not cover all the years[32]. This, in turn, creates issues in the implementation of the identification strategy for treated and control groups since the allocation to one group or the other depends on the credit rating. In order to have a higher number of data points for credit ratings, I decide to pick the most recent available credit rating in the database with respect to the year of interest (i.e. the year when the bank becomes a primary dealer). This seems a reasonable assumption since in most of the cases credit ratings slightly change year by year.

To validate this assumption, I introduce a credit rating model which estimates the bank's credit ratings. If estimated credit ratings from the regression are close enough to the ones I decided to pick as approximation, then I have a confirmation that the approach is correct.

Following the outstanding literature (Beaver 1966; Altman, 1968), I define a list of potential explanatory variables for the model in such a way that they are highly correlated with a bank's probability of default and, in turn, with its credit rating. Most of them are financial ratios since ratios allow for comparisons among companies of different sizes or operating in different countries. Many ratios are highly correlated among them leading to collinearity problems.[33]

The dependent variable of the model is the numerical credit rating of bank *i* and is regressed on the list of explanatory variables defined in the Appendix E. The parameters are estimated using the OLS method. The cross-sectional regression is defined as:

$$
\begin{aligned}
CreditRating_j = \alpha_j + \beta_2 InterestCoverage + \beta_3 Solvency \; + \beta_4 Size + \beta_5 ROA + \\
\beta_6 HostCountryCreditRating + \beta_7 ParentCountryCreditRating + \beta_8 Solvency * \\
HostCountryCreditRating + \beta_9 Solvency * ParentCountryCreditRating + \varepsilon_j
\end{aligned}
$$

In contrast with the outstanding literature on credit rating model I introduce two singular explanatory variables, namely $\boldsymbol{HostCountryCreditRating}$ and $\boldsymbol{ParentCountryCreditRating}$.

[32] Credit rating agencies do not frequently rate private banks.

[33] Stata automatically drops variable in case of collinearity. In addition, heteroscedasticity-robust standard errors are used.

The rationale of this choice is given by the special sample considered for the study. Some primary dealers are subsidiaries incorporated in a host country but owned by a foreign parent bank. Therefore, the rating of this international subsidiary may be affected by macroeconomic and regulatory factors specific to the operating host country, and at the same time, by the credit rating of the country where the parent bank is based. For instance, Barclays Bank Mexico's rating is likely to be influenced by Mexico sovereign because the bank is fully incorporated in the Mexican banking system. However, Barclays is a UK based bank and the Mexican subsidiary credit rating is also correlated to the rating of the UK sovereign. Anginer et al., (2016), in a working paper for IMF, confirms that parents' and international subsidiaries' probability of default are significantly and positively correlated. Moreover, they present regulatory system and macroeconomic factors of the host country as a key driver of the extent to which shocks to the parents distance to default influence subsidiaries. Finally, interaction terms are added since I expect an interaction between Host Country Credit Rating and Parent Country Credit rating and solvency. The higher the credit rating of the country, the higher the solvency of the primary dealer.
Although the results reported in the next section are meaningful and bring interesting insights about credit rating ceiling policy and what drives dealers 'ratings, they also reveal that the number of dealers in the sample with equal or higher credit rating than the sovereign is very small. Therefore, such a small control group poses issues on the credibility of the methodology.

Given this limitation, I adopt the alternative approach discussed in section 5.1 to perform the difference-in-difference analysis and define new treated and control groups.

Credit Ratings Estimated Model

Table 10 presents the estimated model using OLS regression. The credit rating[34] of each PD is regressed on six variables (plus two interaction terms) related to PD financial statements or other risk factors which can impact its probability of default.
Regression model (1) shows the positive and significant relation between the primary dealer credit rating and the sovereign rating of the country where it operates and the country where the dealer's parent is based. A sovereign upgrade of 1 notch in the host country leads to 0.26 higher credit rating while a sovereign upgrade of 1 notch in the dealer's parent country leads to 0.29 higher credit rating. This relation is in line with expectations defined in the methodology

[34] When the credit rating is not available for the year of interest, the most recent one is selected.

section 4.2. *Interest coverage* ratio coefficient is positive and significant meaning that one extra unit of interest coverage ratio increases PD credit rating by 0.37 notches. This positive relation is in line with expectations since interest coverage is a measure of financial distress, showing dealer's ability to make interest payments on its debt in a timely manner. *Solvency* coefficient is unexpectedly negative and significant. This is counterintuitive since I expect that the more solvent a bank is, the higher the credit rating.

Size and *ROA* are not significant. The coefficients and their significance present some anomalies with respect to the outstanding literature. Size or profitability of a company should have a positive impact on its probability of default. However, the dataset of the research is somewhat particular. Primary dealers are usually big banks, which operate worldwide, and they are all subjected to minimum capital and profitability requirements. Therefore, it is intuitive that there is no significant variation within the sample used in this study.

Regression model (2) and (3) introduces interaction terms. Their coefficients are not significant in both models but they help to explain the counter-intuitive negative and significant coefficient for *solvency*. In both models (2) and (3), after inclusion of the interaction terms, *Solvency* coefficient turns positive, as expected, but it is not significant. The coefficient is the effect of *Solvency* on the primary dealer credit rating given the average value of country credit rating[35]. A positive but not significant coefficient is what I expect given that there is minimum or no variation at all within the sample. *Both* interaction terms show negative and not significant coefficients. A negative and significant coefficient would mean that, the higher the country credit rating (host or parent), the lower (more negative) the effect of solvency on the primary dealer credit rating. Vice versa, the higher the solvency, the lower (more negative) the effect of the country credit rating on the primary dealer credit rating. Table 11 provides a more detailed analysis using as example the marginal effects of *Solvency* on PD credit rating at different levels of the host country sovereign rating. *Solvency* has a significant and negative impact on PD credit rating for levels of host country sovereign ratings between BBB- and AA-. The insignificant relation at other levels is bringing the overall significance down. The same analysis conducted using parent country sovereign sating provides similar results and it is not reported here.

[35] In model (2) Solvency is the net effect on PD credit rating regardless the influence of the host country sovereign rating while in model (3) Solvency is the net effect on PD credit rating regardless the influence of both host and parent country sovereign ratings.

Table 10

Credit Rating Estimated Model

This table presents OLS regression estimates of the effect of selected financial statement variables and country credit ratings on primary dealers credit rating, which is numerically converted. The sample is made of 152 primary dealers. Variable definitions are provided in Appendix E. *, **, *** indicates significant coefficients respectively at 10%, 5% and 1% according to the heteroscedasticity-robust t-statistic.

PD Credit Rating	(1)	(2)	(3)
	Coef.	Coef.	Coef.
Host Country Credit Rating	0.26***	0.43***	0.36***
(Country where dealer operates)	(0.08)	(0.14)	(0.78)
Interest Coverage	0.37**	0.46***	0.51***
	(0.18)	(0.18)	(0.18)
Solvency	-8.25**	10.11	21.94
	(3.36)	(14.33)	(19.71)
Size	0.01	-0.04	-0.06
	(0.07)	(0.08)	(0.09)
Roa	-7.41	-5.31	-9.92
	(15.38)	(14.28)	(14.90)
Parent Country Credit Rating	0.29***	0.29***	0.44***
(Country where parent dealer operates)	(0.07)	(0.07)	(0.12)
Host Country Credit Rating*Solvency		-2.25	-1.64
		(1.79)	(1.69)
Parent Country Credit Rating*Solvency			-1.43
			(1.06)
Observations	152	152	152
R-squared	37.77%	38.85%	39.54%

Table 12 presents an interesting post-analysis of the model and shows that almost 90% of the credit ratings estimated by the model are within 3 notches of distance from the ones that I picked as approximation released by the international credit agencies.

Table 11

Marginal Effects of Solvency conditional on Country Credit rating

Plot of marginal effects of solvency on primary dealer credit rating at different levels of country credit rating.
*, **, *** indicates significant values respectively at 10%, 5% and 1% according to t-statistic. Robust standard errors are reported in parenthesis.

PD Credit Rating	**Solvency**	
	Coefficient	**Standard Error**
At Country Credit Rating		
1	2.11	(11.49)
3	-1.17	(8.32)
5	-4.46	(5.41)
7	-7.75**	(3.46)
9	-11.04***	(4.18)
11	-14.33**	(6.76)
13	-17.62*	(9.84)
15	-20.90	(13.06)

Table 12

Distance between Predicted and Observed Ratings

This table presents the frequency distribution of the distance between the credit ratings predicted by the model and the ones picked as approximation issued by the international credit agencies.

Distance (Notches between Predicted and Observed Rating)	%	%Cumulative
0	17.12	17.12
1	32.88	50.00
2	21.92	71.92
3	14.38	86.30

The fact that predicted and actual ratings are close to each other's validates the model and its precision in replicating ratings. Figure 8, reported in next page, provides an additional description of the model output[36]. The plot exhibits the frequency distribution of the difference between the predicted ratings and the observed ones, issued by the rating agencies.

This analysis brings another interesting result. Approximately 86% of the banks' estimated credit ratings are within 3 notches distance with respect to observed ones. It is also important to consider that most of the banks with higher rating than the sovereign are foreign subsidiaries

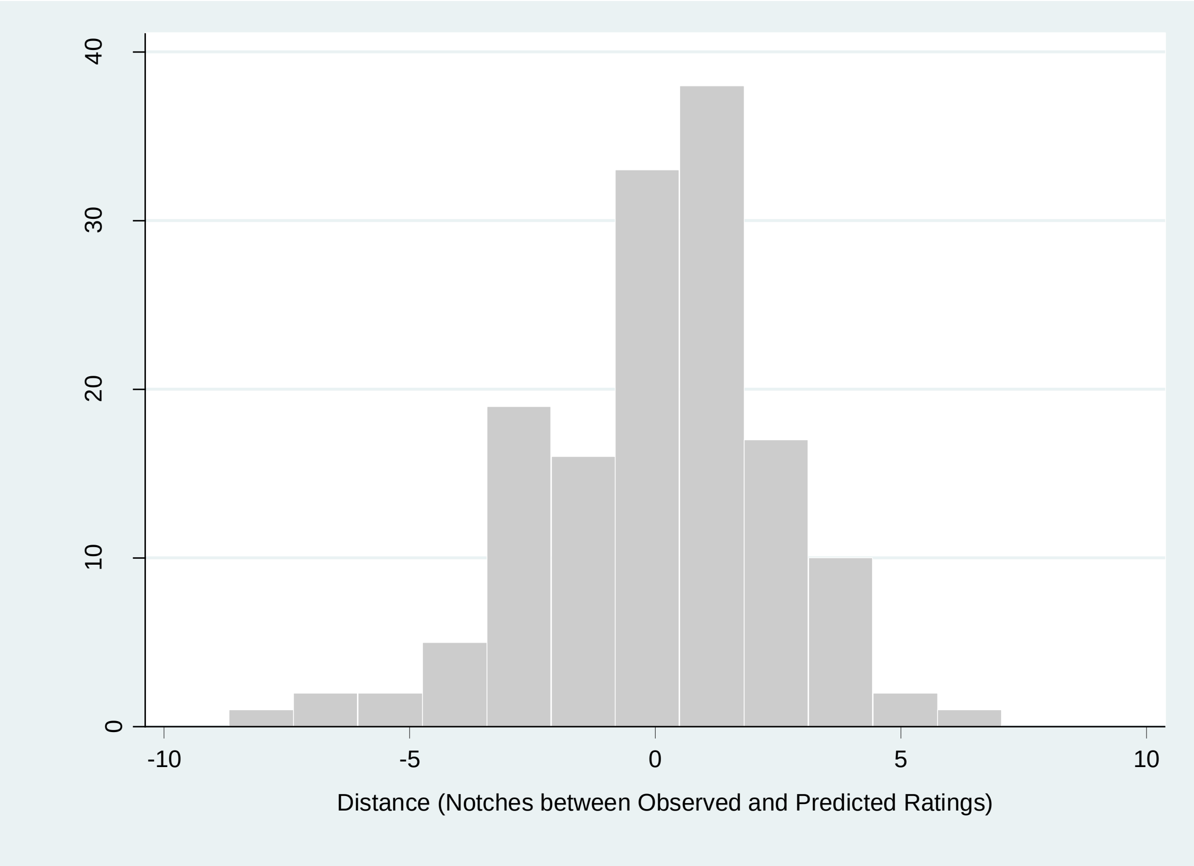
[36] I follow Grün et al., (2010) methodology for presenting data about the distance between predicted and observed ratings.

of international banks operating in emerging countries. Therefore, it is easy for them to be rated higher than the sovereign of an emerging country. Overall, only 28.5% of the dealers have a credit rating higher or equal than the sovereign posing an issue for the following difference-in-difference analysis. Indeed, the control group, made of dealers with higher or equal credit rating than the sovereign, is not sufficiently large to conduct a reliable analysis.

Figure 8

Frequency Distribution of Credit Rating Regression Residuals

Plot the frequency of the difference between predicted credit ratings by the model and actual ones. The difference corresponds to the residuals of the model and is expressed as the number of notches separating the two ratings.



APPENDIX B: List of Countries

Table 13

List of Countries

This table presents the list of the countries analyzed for the study and the relative number of primary dealers. Primary dealership is introduced in different years for different countries.

Country	Implementation Date	Primary Dealers	Authority	Supervision
Belgium	1991	12	Treasury	Belgian Debt Agency
Bulgaria	2007	15	Ministry of Finance	Bulgarian National Bank
Czech Republic	1997	14	Ministry of Finance	Ministry of Finance of Czech Republic
Denmark	2004	6	Central Bank	Denmark Nationalbank
Spain	1988	3	Ministry of Finance	Ministry of Finance
Greece	1998	5	Ministry of Finance	Public Debt Management Agency
Hong Kong	2009	6	Ministry of Finance	HKSAR Government
Hungary	1996	13	Ministry of Finance	AKK Government Debt Management Agency
Italy	1994	14	Ministry of Finance	Dipartimento del Tesoro
Lithuania	2001	9	Central Bank	Lietuvos Banks
Latvia	2013	4	Ministry of Finance	Ministry of Finance
Mexico	2000	11	Central Bank	Banco de Mexico
Netherlands	2001	4	Ministry of Finance	Dutch State Treasury Agency
Norway	1995	8	Central Bank	Norges Bank
Portugal	1998	10	Ministry of Finance	Portuguese Treasury and Debt Management Agency (IGCP)
Sweden	1989	3	Central Bank	Finance Supervisory Institution
Singapore	1987	7	Central Bank	Central Bank
Slovenia	2006	6	Ministry of Finance	Central Bank
Turkey	2002	11	Ministry of Finance	Undersecretariat of Treasury
South Africa	2000	7	Central Bank	National Treasury Republic of South Africa

APPENDIX C: Event Study

Test Statistics

Crude Dependence Adjustment t-test (CDA T)

To test the significance of the average abnormal return on a single day (H0: AAR=0) the t-test is given by

$$t_{AARt} = \sqrt{N}\frac{AAR_t}{SD_{AAR}}$$

where SD_{AARt} is the standard deviation of abnormal average returns across the sample over the estimation window of length T = ($T_1 - T_0$) and is defined as

$$SD_{AARt} = \sqrt{\frac{1}{T}\sum_{t=T0}^{T1}(AAR_t - \overline{AAR_t})^2}$$

To test the significance of the cumulative average abnormal return (H0: CAAR=0) the t-test is given by

$$t_{CAARt} = \frac{CAAR}{\sqrt{T_2 - T_1}SD_{AAR}}$$

Where $T_2 - T_1$ is the length of the event window.

Corrado Rank-Test (Rank Z)

To obtain the Corrado rank-test the abnormal return of each company is converted into a rank. This process applies to the abnormal returns of both the estimation and the event period. If ranks are tied, the midrank is used. Following the procedures illustrated by Corrado and Zyvney (1992), ranks are standardized by the length of the combined estimation and event period (T_i).

$$K_{i,t} = \frac{rank(AR_{i,t})}{1 + T_i}$$

To test the significance of the average abnormal return on a single day (H0: AAR=0) the rank-test is defined as:

$$t_{RANKaar} = \frac{\frac{\sum_{i=1}^{Nt} K_{i,t}}{N_t} - \frac{1}{2}}{SD_{\overline{K}}}$$

where N_t is the number of non-missing returns across the sample over one day and $SD_{\overline{K}}$ is given by

$$SD_{\overline{K}} = \sqrt{\frac{1}{T}\sum_{t=0}^{T2}\left(\frac{\sum_{i=1}^{Nt} K_{i,t}}{N_t} - \frac{1}{2}\right)^2 \frac{N_t}{N}}$$

To test the significance of the cumulative average abnormal return, H0: CAAR=0 the t-test is given by[37]

$$t_{RANKcaar} = \frac{\frac{\sum_{t=T1+1}^{T2} \overline{K_{T1,T2}}}{L2} - \frac{1}{2}}{SD_{\overline{K}}}\sqrt{L2}$$

where L2 is the length of the event window. I vary the length of L2 to obtain different test statistics over different event windows.

Table 14

Abnormal Returns: Primary Dealers

This table presents abnormal return around the announcement of the inclusion into the primary dealerships of 66 international banks. The numbers in the table are the mean or median of the abnormal return over the event window (-30, 30). *, **, *** indicates significant values of mean or median respectively at 10%, 5% and 1% according to the t-statistic. Cross-sectional standard errors are reported in parenthesis.

	AAR	
	Market Model	
Event Day	Mean	Median
-30	-0.0004	-0.0001
-29	0.00265***	-0.0007
-28	0.00169***	0.0004
-27	0.00274***	0.0002
-26	-0.00184***	-0.00097**
-25	0.00179***	0.00196***
-24	0.00137***	0.00244***
-23	0.00177***	0.0003
-22	0.00367***	0.00304***
-21	0.0009**	-0.00108**
-20	0.002***	0.00129***
-19	-0.00217***	-0.0001
-18	-0.00138***	0.0005
-17	-0.00178***	-0.00102**
-16	-0.0005	-0.00076*
-15	0.00141***	-0.00076*
-14	-0.00141***	-0.00076*
-13	-0.00699***	-0.00332***
-12	0.0002	0.0000
-11	-0.0005	-0.00071*
-10	-0.0025***	-0.00122***
-9	0.00194***	0.00179***

[37] The rank-test statistic for multiday event period was introduced by Campell and Wasley (1993).

-8	0.0052***	0.00184***
-7	0.0004	0.0003
-6	-0.0007	-0.0006
-5	0.00132***	0.00138***
-4	0.00399***	0.0041***
-3	0.00115**	-0.0013***
-2	0.0000	-0.00148***
-1	-0.0003	-0.0005
0	0.0006	-0.0006
1	0.00377***	0.00254***
2	0.00304***	0.00141***
3	0.0005	0.00115***
4	-0.00219***	-0.00211***
5	0.0006	0.00139***
6	0.00443***	0.00221***
7	-0.0002	0.00082*
8	0.00087**	0.00086**
9	0.0003	0.00075*
10	0.00221***	0.0001
11	0.00382***	0.0003
12	0.00491***	0.00213***
13	0.00441***	0.00406***
14	-0.0001	0.0002
15	0.00106**	0.00211***
16	0.00351***	0.00102**
17	-0.00313***	-0.00151***
18	0.00134***	-0.00277***
19	-0.0002	-0.00118**
20	-0.0002	0.0003
21	0.00158***	0.00154***
22	0.0002	0.00097**
23	-0.00088***	0.0006
24	-0.00145***	0.0000
25	0.0001	-0.0003
26	0.0004	0.00191***
27	0.00232***	0.0005
28	-0.0008*	0.0001
29	0.00171***	0.00119**
30	-0.00389***	-0.00235***

Table 15

Cumulative Abnormal Returns of Primary Dealers

This table presents cumulative abnormal return around the announcement of the inclusion into the primary dealerships of 66 international banks. The numbers in the table are the mean or median of the cumulative abnormal returns over different event windows. *, **, *** indicates significant values of mean or median respectively at 10%, 5% and 1% according to the time-series standard deviation t-statistic (1) or Corrado rank t-statistic (2).

	CDA T-test		Rank T-test	
Window	Mean	Median	Mean	Median
[-30,-1]	1.38%	0.42%	1.38%	0.42%
[-10,-1]	1.05%	0.43%	1.05%	0.43%
[-5,-1]	0.62%	0.22%	0.62%	0.22%
[0,+1]	0.44% *	0.20%	0.44%	0.20%
[0,+3]	0.79% *	0.45%	0.79%	0.45%
[0,+5]	0.64%	0.38%	0.64%	0.38%
[0,+10]	1.39% *	0.85%	1.39%	0.85%
[0,+15]	2.8% ***	1.73% *	2.8% *	1.73% *
[0,+20]	2.93% ***	1.31%	2.93%	1.31%
[0,+30]	2.86% **	1.72%	2.86%	1.72%

APPENDIX D: Credit Ratings Mapping

Table 16

Mapped Credit ratings

This table shows how credit ratings by Moody’s, S&P and Fitch are mapped into numerical categories ranging from the highest one (16) to the lowest (1).

Moody's	S&P	Fitch	
Long-term Cedit Rating			Numerical category
Aaa	AAA	AAA	16
Aa1	AA+	AA+	15
Aa2	AA	AA	14
Aa3	AA−	AA−	13
A1	A+	A+	12
A2	A	A	11
A3	A−	A−	10
Baa1	BBB+	BBB+	9
Baa2	BBB	BBB	8
Baa3	BBB−	BBB−	7
Ba1	BB+	BB+	6
Ba2	BB	BB	5
Ba3	BB−	BB−	4
B1	B+	B+	3
B2	B	B	2
B3	B−	B−	1

APPENDIX E: Variable Definitions

Table 17

Variable Description

Variable	Definition
Interest Coverage	Ratio of EBIT to total interest expenses (Bankscope Items 10220/10070)
Size	Logarithm of total assets in billions of U.S. dollars (Bankscope item 2025).
Roa	Ratio of net income to total asset (Bankscope 10285/2025)
Country Credit Rating	Long-term sovereign rating mapped into 16 numercal categoriesBnakscope and Bloomberg
Size	Logarithm of total assets in billions of U.S. dollars (Bankscope item 2025).
Profitability	Operating income divided by total assets (Bankscope items 4024/2025).
Solvency	Ratio of common equity to total assets (Bankscope items 2055/2025).
Liquidity	Ratio of cash and marketable securities to total assets (Bankscope items 2075/2025)
Credit Rating	Long-term issuer credit rating mapped into 16 numrical categories (Bankscope and Bloomberg).
Deposits	Ratio of deposits and short-term funding to total assets (Bankscope items 2030/2025)
Interbank Funding	Ratio of deposits from banks to lagged total funding (Bankscope items 2185/11650)
Non-Deposit Short-Term Funding	Ratio of deposits and short-term funding minus deposits to lagged total funding (Bankscope items (2030−2031)/11650).
Retail Deposits	Ratio of customer deposits to lagged total funding (Bankscope items 2031/11650)
Growth of Total Assets	Bankscope item 18190
Long-Term Funding	Ratio of long-term funding to lagged total funding (Bankscope items 11620/11650).

APPENDIX F: Difference-in-difference Graphs

Figure 9

Plot of Year-by-year *Growth of Total Assets* for years before, during, and after entering the primary dealership. Percentage average of the ratio over time is reported for both treated and control units.

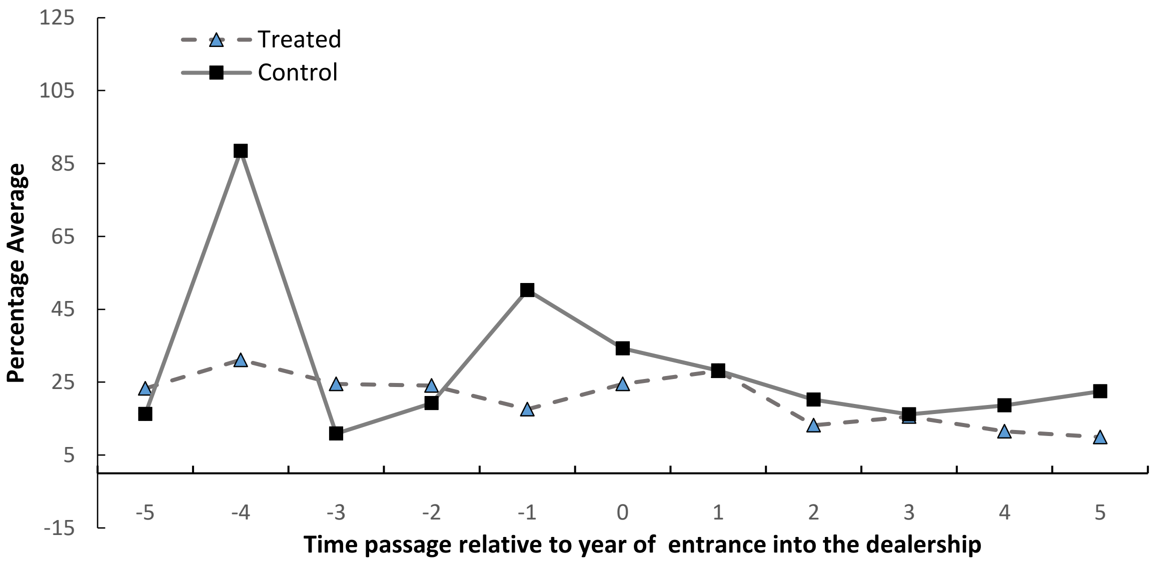


Figure 10

Plot of Year-by-year *Retail Deposits* for years before, during, and after entering the primary dealership. Percentage average of the ratio over time is reported for both treated and control units.

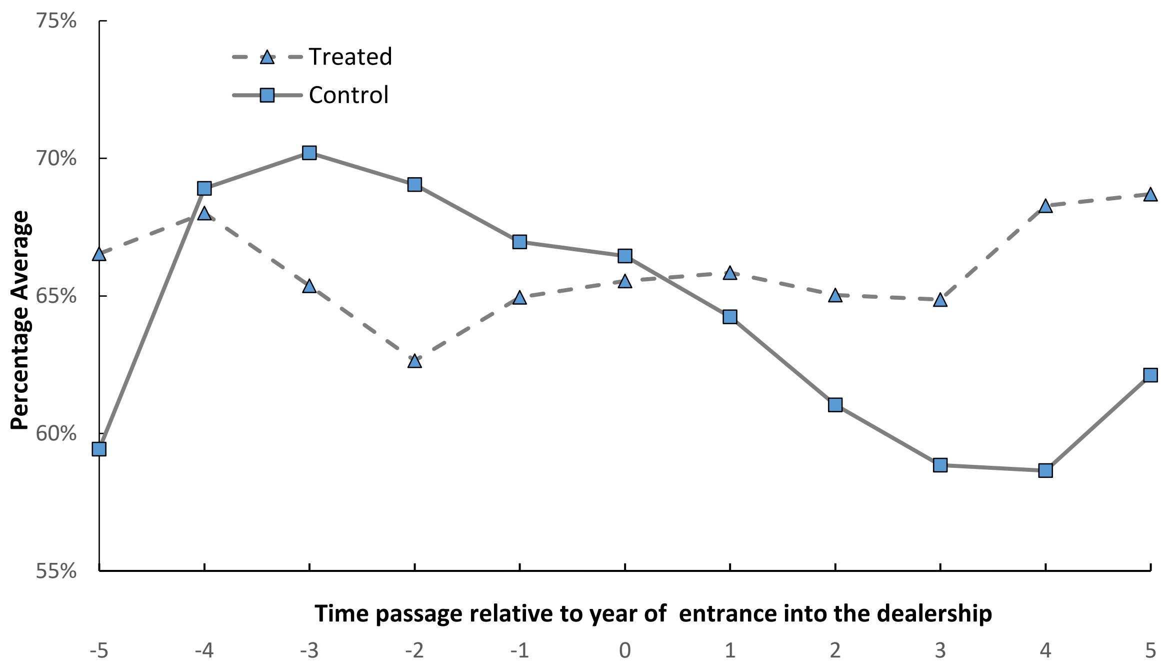


Figure 11

Plot of Year-by-year *Non-Deposit Short-Term Funding* for years before, during, and after entering the primary dealership. Percentage average of the ratio over time is reported for both treated and control units.

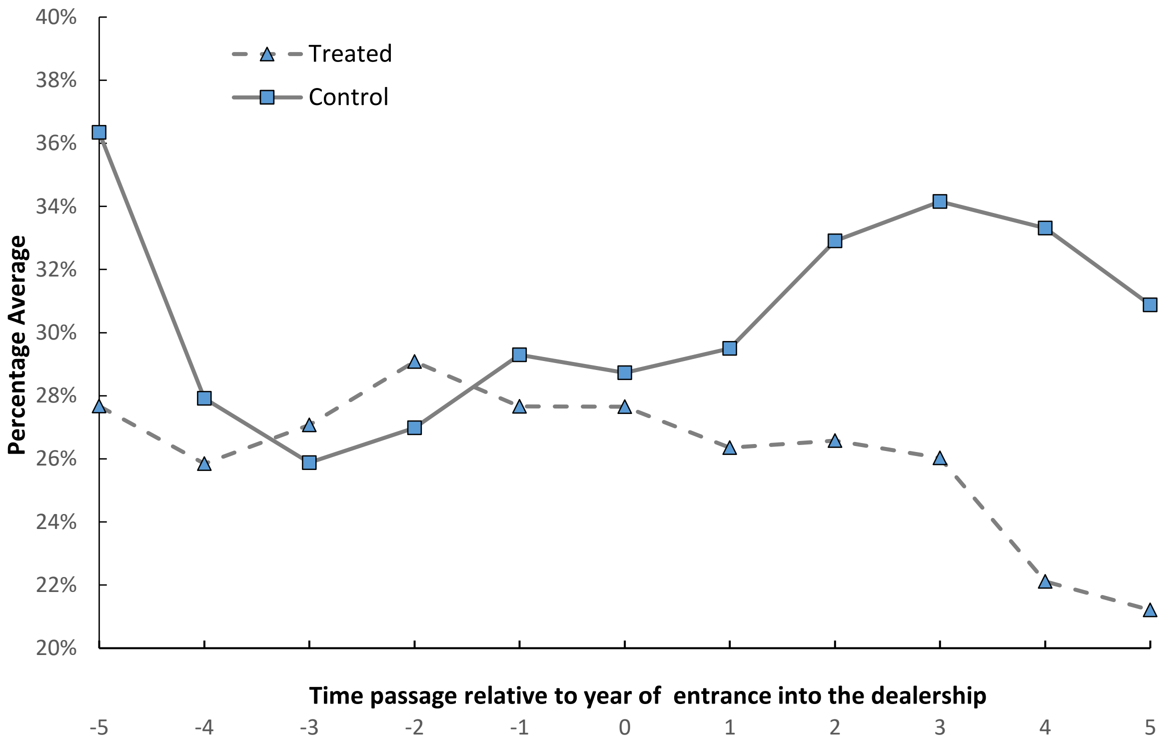


Figure 12

Plot of Year-by-year *Interbank Funding ratio* for years before, during, and after entering the primary dealership. Percentage average of the ratio over time is reported for both treated and control units.

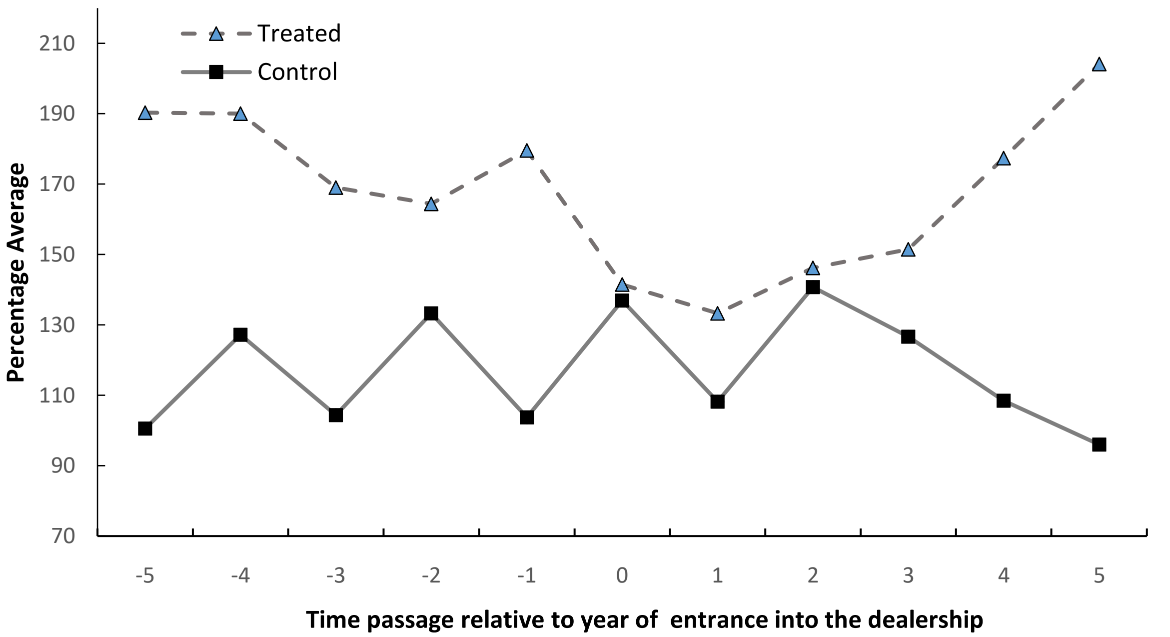


Figure 13

Plot of Year-by-year *Long-term Funding* for years before, during, and after entering the primary dealership. Percentage average of the ratio over time is reported for both treated and control units.