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Four Essays on Hidden Risks into the Global Financial Architecture

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To my parents Teresa and Osvaldo and to my cat Puffetta

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Abstract

The doctoral dissertation of Laura Gianfagna, Ph.D. Candidate in Economics at IMT School for Advanced Studies Lucca, is submitted at IMT School for Advanced Studies Lucca. The original research thesis studies unsolicited weak points of the current Global Financial Architecture and unknown sources of financial contagion. The dissertation provides policy advice and innovative methodologies to improve the current financial supervisory monitoring.

The main topics covered are credit risk and financial risk. On the credit risk side, the author addresses two issues: a lack of regulatory supervision for Multilateral Development Banks and a model risk that the economic capital calculation for portfolio credit risk and the regulatory capital calculation for counterparty credit risk have in common. On the financial risk side, the thesis estimates a significant impact of corporate control on stock market volatility. The empirical investigation confers the right to exist to an entity acting on financial market prices through the property channel, in parallel to business groups. An innovative methodology is then applied to the Interest Rate Swap market to detect correlation and co–movements among its subclasses aggregated by contractual characteristics. All the results contribute to the research literature on early warning triggers for systemic risk.

Executive summary

The *Global Financial Architecture* is an agreed set of rules on the capital markets among the financial institutions that govern the vast majority of the World Gross Domestic Product. The adjective *global* refers to the global prosperity and stability purpose that accompanied the historical process of creation of a unified and transparent regulatory environment for financial markets, as well as the policy responsibilities over the occurrence of the economic globalization. The role of the Economists is precisely providing policy advice stemming from exact research investigation: Economists propose theories and models to capture general equilibrium[1] as well as market frictions and asymmetries and financial markets imperfections[2]. Financial Economists acknowledge the difficulties of keeping financial markets stable from volatility and the persisting effects of financial crises on the economy. Financial stability has become a major concern to policymakers as a precondition to a sustainable economic growth since the distinction between business and financial cycles that run in parallel at different frequency[3]. Macroprudential regulation brought the international attention on the Global Financial Architecture after detecting systemic risk as the fertile ground for the propagation of

[1]See e.g. Walras (2013), Smith (1976), Keynes (2016), Nash (1950), Arrow and Debreu (1954), Modigliani and Miller (1958), Sharpe (1964), Tobin (1969), Arrow (1971), Cox et al. (1985), Merton (1987), Longstaff and Schwartz (1992), Debreu (1996).

[2]See e.g. Jaffee and Stiglitz (1990), Minsky (1977), Greenwald and Stiglitz (1993), Stiglitz (1999), Bernanke et al. (1999), Almeida et al. (2004), Krugman (2009).

[3]See e.g. Borio and Lowe (2002), Borio (2014).

financial and economic shocks[4]. Nevertheless, recent regulatory developments for financial intermediaries issued by international supervision bodies highlight the necessity of further research, explanations, and policy advice from the Academic sector.

The dissertation contributes to this goal by assessing four hidden risks into the Global Financial Architecture. The research thesis encompasses four essays, equally divided into theoretical and practical investigations. The first and the last essays of the dissertation compare the models used in banking practice and financial regulation and the scope of the financial regulation, respectively. Two intermediate essays quantify a source of corporate financial contagion and a distress measure for derivative markets, respectively. More precisely, chapters 1 and 4 address the international regulation for financial institutions and point out two severe shortages for the assessment of credit risk: lack of an independent model testing for financial institutions and high reliance on Credit Rating Agencies for regulatory requirements the first, and lack of a unified international regulatory supervision for Multilateral Lending Institutions the second. Chapter 2 and chapter 3 address the financial instability by discovering a channel for the propagation of volatility across financial markets and a methodology to order co–movements among submarkets according to their riskiness. A closer focus on each chapter is now detailed.

Chapter 1 proceeds to address the usage of Merton's model and examining the role of information into financial default models. One question is how information is transposed into the models used for assessing credit risk. The exercise answers that structural–form models are the most employed into the current banking practice. This kind of model assumes that both the market and the corporate have real–time access to the most available information and it reflects the complete informa-

[4]See e.g. on Global Financial Architecture Levine (1997), Daniel (2017), Hofmann et al. (2017), UNCTAD (2015), and on systemic risk Tarashev et al. (2009), Caruana (2010), Acharya et al. (2017). An interesting commentary is provided by `https://piie.com/commentary/speeches-papers/reshaping-global-financial-architecture`.

tion in the calculation performed for the credit risk assessment. In this framework, every external shock is exogenous to the model, that must re–adapt its parameters to encompass the new condition. Furthermore, these models focus on hypotheses, such as the normality assumption on the distribution of losses or the reliance on external credit ratings, that result too poorly conservative for risk management purposes. Another question is the scope of application of the same model to different risk assessments. If several risk metrics rely on the same methodology, this could raise an issue on the correct risk assessment. The thesis assesses such an issue between regulation and banking practice.

Another regulatory shortcoming is posed by chapter 4, that addresses the lack of a unified supervision for Multilateral Development Banks. Because of the lack of financial regulatory regime their current operating framework is not comparable to the regulated banking sector. It also entails credit risk since standardized credit risk assessment is a precondition for a smooth lending environment in which banks have not to do credit rationing or shrink their assets to save capital, especially in low–capital markets environment where the traditional banking lending still prevails. After the financial crisis of 2007–2008 this was instead the case for advanced economies, especially the Euro area, frightened by an enormous amount of non–performing loans and small margins. A consequence has been the increasing recourse to extraordinary funding provided by Multilateral Development Banks (MDBs). Given the massive movement of money across worldwide borrowers, should MDBs be internationally regulated?

Chapter 2 identifies the corporate ownership relationship with a well–defined entity acting on listed markets as a channel for the propagation of the financial volatility of stock market prices. The unique worldwide dataset and the research methodology allow for an accurate identification of correlations within a parent company and its affiliates over time and across countries for both domestic and MultiNational Enterprises (MNEs). The methodology is tested against different volatility metrics and can be readily generalized to multi–layered business groups. The results show less variance at a group level than across firms and time, and price activities show a narrower range of volatility when a hierarchy of companies is established. This is likely due to information on the common fundamentals that is passed to investors when the latter consider all the companies as a unique entity. A consequence is that a shock occurring in one affiliate can move faster to its co–affiliates, within one country in case of a domestic group, and across countries, in the case of MNEs.

Chapter 3 is the first empirical research on systemic risk assessment based on micro-founded Interest Rate Swaps (IRS) data from a trade repository. It studies the relationship among subsegments of a financial market as a way to identify potential financial distress through increased co–movements among them. The combination of granular data on Over-The-Counter (OTC) derivatives and a Joint Probability of Distress (JPoD) methodology let define a *distress indicator* that combines several distress drivers. The results put similarities between financial and contractual terms as responsible for stronger co–movements among submarkets. However, high values for JPoD even in correspondence of dissimilar sub-markets suggest the presence of other drivers that should be investigated in future research.

Tackling hidden risks into the Global Financial Architecture is a complex challenge that requires both micro and macro approaches. The matter and its scope range from corporate finance to financial markets and from a single market to international Economics respectively. The instances covered by the doctoral thesis reflect this broad spectrum of topics, and they expand into four essays regarding credit risk and financial risk. The rationale linking the four of them is the awareness that a proper risk assessment is at the baseline of discovering sources of systemic risk or early warning triggers for the Global Financial Architecture.

Since systemic risk is a relatively new field of research, in the future more effort could go into comparing the estimators for systemic risk and other types of risk and estimating the impacts in figures that each source of concern delivers, so to quantitatively assess the proportion of systemic risk due to other risks. Such an estimation would be beneficial to systemic risk that is by its nature tightly related to the sources of other hazards. However, definition and measurement of systemic risk have still to proceed on their own in the research literature. Therefore it is not wasted a preliminary focus on the background matters, foreseeing their future application and a vast work left to future studies.

Chapter 1

Rating and pricing: state of the art for the proposal of new methodologies

1.1 Introduction

The first essay of the dissertation will guide the reader through the concept of financial risk by pointing out an evident - yet undiscovered - relationship among the main model on which important pricing dynamics are based. What is a financial risk, which branches of risk management it involves, why it can stem from credit risk will be explained. The novelty of the research is discovering the dynamics through which credit risk may generate a financial risk by affecting the pricing methodologies of financial contracts. Such a dynamics has a common and evident denominator, namely the mathematical models based on normality assumptions. To introduce this dynamics, firstly the definitions of financial and credit risks will be clarified; secondly, the process through which the two risks are related will be described. The thesis is that this relationship constitutes a financial risk itself because of self-referentiality of the models. Self-referentiality of the models entails two channels: Merton's models that assume a conditional normal distribution of losses and credit ratings.

While credit ratings have been proved as a not sufficient methodology for credit risk purposes because of being static[1], the former issue has never been made clear enough to the best of authors' knowledge. The hypothesis of normality is quite common, but it excludes the case of fat tails of the loss distribution that can generate damage to the economy more severe than expected. Although there is evidence that the normality assumption is unrealistic in some cases[2], the vast majority of financial models, especially the regulatory ones, rely on it. Models based on world-normality assumption range from credit risk and counterparty credit risk models to interest rate risk models, GARCH time series, Bayesian inference, Dynamic Stochastic General Equilibrium models. This chapter will cover some of them, leaving a major revision of all the models based on normality assumptions to future work.

This chapter will focus on the systematic self-referentiality of the credit risk management framework by explaining the credit rating issue and by focusing on Merton's historical passage that ties credit risk to counterparty credit risk. Merton's model is a revolutionarily brilliant discovery; nonetheless, the nexus detectable through several practices can raise a major consequence on financial and credit markets because of its extensive application producing arbitrages and because of no test against different underlying models. The situation is exacerbated by the current regulatory regime regarding counterparty credit risk, requiring banks to compute regulatory capital with the same methodology used for credit portfolio models and pricing. In the current setting, banks' stress testing becomes an active measure for model calibration and the only source of backtesting. Instead, going to the roots of the models, many possibilities are envisaged to provide an alternative route of mathematical modeling. This will be given at the end of the chapter in section 1.6. Section 1.2 poses

[1] See e.g. the assessment of Hilscher and Wilson (2016).

[2] The normality assumption has been proved to be misleading for risk management. E.g., Danielsson and de Vries (1997) show that models based on conditional normality are not well suited to estimating large quantiles of the profit and loss distribution. McNeil and Frey (2000) confirm that an assumption of conditional normality of residuals is unrealistic for the strictly stationary time series representing daily observations of the negative log return on a financial asset price.

the research question by clarifying the main terminology and explaining the key passage that binds counterparty credit risk and a financial systemic risk through the pricing *la Merton*. Merton's framework will be analysed in section 1.4 after an overview in section 1.3 of main credit portfolio models that heavily rely on it Merton's model. Then the regulatory perspective on counterparty credit risk methodology of section 1.5 will provide an example of pricing and rating issues. For a better understanding of how the issues are linked a conceptual map of the chapter is presented in figure 1.

1.2 Research question and related literature

The research question can be summarized as the theoretical investigation of a self-referentiality of models assessing different kinds of risk. To introduce this self-referentiality we explore the nexus between credit and financial risks. A financial risk expresses the investor's uncertainty of collecting returns and the possibility of monetary loss. On a vast scale, monetary losses may affect the real economy; by contrast, not necessarily a financial risk stems from economic conditions or dynamics. Often a financial risk is triggered either by the incorrect evaluation of investment solutions or by unpredictable accidents not related to the financial sector. To Nobel Prize Sir Robert Merton, Economics would be sufficient to describe and manage financial transactions across agents and Countries if no risks were existing. Financial risk cannot be deleted but it has to be transferred: this is the main objective of Finance. The financial risk related to a creditor's solvency or a portfolio worthiness is addressed by Credit risk. The document Basel Committee on Banking Supervision (2000) sets the aim of credit risk for banks: maximise the risk-adjusted rate of return by maintaining the credit risk exposure within acceptable parameters. Maintaining the credit risk exposure within acceptable parameters requires a risk assessment of the portfolio and of single counterparts. When counterparts are subject to rating assessment by the Credit Rating Agencies (CRAs) then the evaluation of a creditor's worthiness may be based upon those external rating already assigned to creditors. The output process of a creditor evaluation serves as a basis for the pricing of unexpected losses or derivative contracts. Derivatives (such as futures, forwards, swaps, options, credit derivatives, mortgage-backed security) are made between two financial parties for many purposes. Derivatives are used for hedging (e.g., insuring against risk on an asset or circumventing exchange rate issues) or for speculation in betting the future price of the underlying asset. The value of these securities depends on one or more underlying assets such as stocks, bonds, commodities, currencies, interest rates and market indexes; that is why most derivatives are traded Over-The-Counter (OTC) rather than on a regulated exchange. Such contracts are created to transfer the risk, inasmuch they reduce the risk related to changes in the value of the underlying asset. Investors buy derivative contracts to protect against the possibility of a monetary loss. The attribution of a correct price to such notes is therefore extremely important: it is meant to reflect a proper risk assessment, and it can be derived from the price of the underlying.

The process of the attribution of an unbiased price is called pricing. Modern pricing theory reveals that a correct pricing is equal to the discounted expected value of the future payoff of the derivative; the expectation is computed not under the physical probability of future events, but under a new risk-neutral measure that turns the stochastic process of price of the underlying into a martingale[3] (Karlsen (2010), Hull (2006)). A proper pricing should not give room to endogenously created market arbitrage. Following the definition of Björk (2009), a market arbitrage happens when it is possible to purchase and sell the same security at the same time in different markets to take advantage of a price difference between the two separate markets. This is equivalent to the possibility of making a positive amount of money out of nothing without taking any risk: a free lunch on the financial market. Arbitrage possibilities represent a case of mispricing in the market. Efficient markets show no arbitrages:

[3]A martingale process realizes, at discrete-time, when the conditional expected value of the next observation, given the past observations, is equal to the most recent past observation.

if any, they would (or tend to) clear reciprocally[4]. Market arbitrages can be positive, neutral or dangerous. Literature has found that sometimes temporary arbitrages are useful to bypass market *anomalies*, such as when they favour the offsetting of excess or deficiency falls of equity returns into the liquidity market[5]. Nevertheless, arbitrage is found to become ineffective in extreme circumstances when prices diverge far from fundamental values (Shleifer and Vishny (1997)). Furthermore, higher degrees of arbitrage risk is correlated to anomalies persistent over an extended period of time[6]. Therefore, through arbitrages, severe or repeated mispricing can lead to market imbalances. The cumulative process of deviations of key variables from trends contribute to the build-up of vulnerabilities, alter the financial cycle and may harm the equilibrium of the global financial architecture[7].

This chapter will study the nexus between credit risk and the financial risk given by a possibility of derivatives (mis)pricing due to model risk. In this case, model risk is not the risk that the model is wrong per se, but market arbitrages due to the same model applied to estimate credit risk. Regulatory prescriptions focusing once more on the same underlying model create a nexus between credit risk and counterparty credit risk; some recurrent aspects among the methodologies are highlighted as a possible source of market biases because of models' systemic self-referentiality. Merton's model is the most used for credit portfolio risk. Since more than thirty years, the Black-Scholes-Merton models are also part of the best banking practice of every financial institution. Banking regulation is heavily relying on them. Although this evidence is there for all to see, to the best of authors' knowledge this is the first time that a model issue is pointed out with both regulatory and mathematical details. The author emphasizes a positive correlation between credit risk, that is the possi-

[4]The fundamental theorem of asset pricing is assumed. According to it, a market is efficient if no arbitrage is possible. See more e.g. in Dybvig and Ross (2003).

[5]See Chordia et al. (2014).

[6]See in Chou et al. (2013) the case of trading volume.

[7]Suggested literature about market vulnerabilities leading to bouts of financial instability includes Arnold et al. (2012), Obstfeld and Rogoff (2009), Acharya et al. (2017), Caballero and Krishnamurthy (2009).

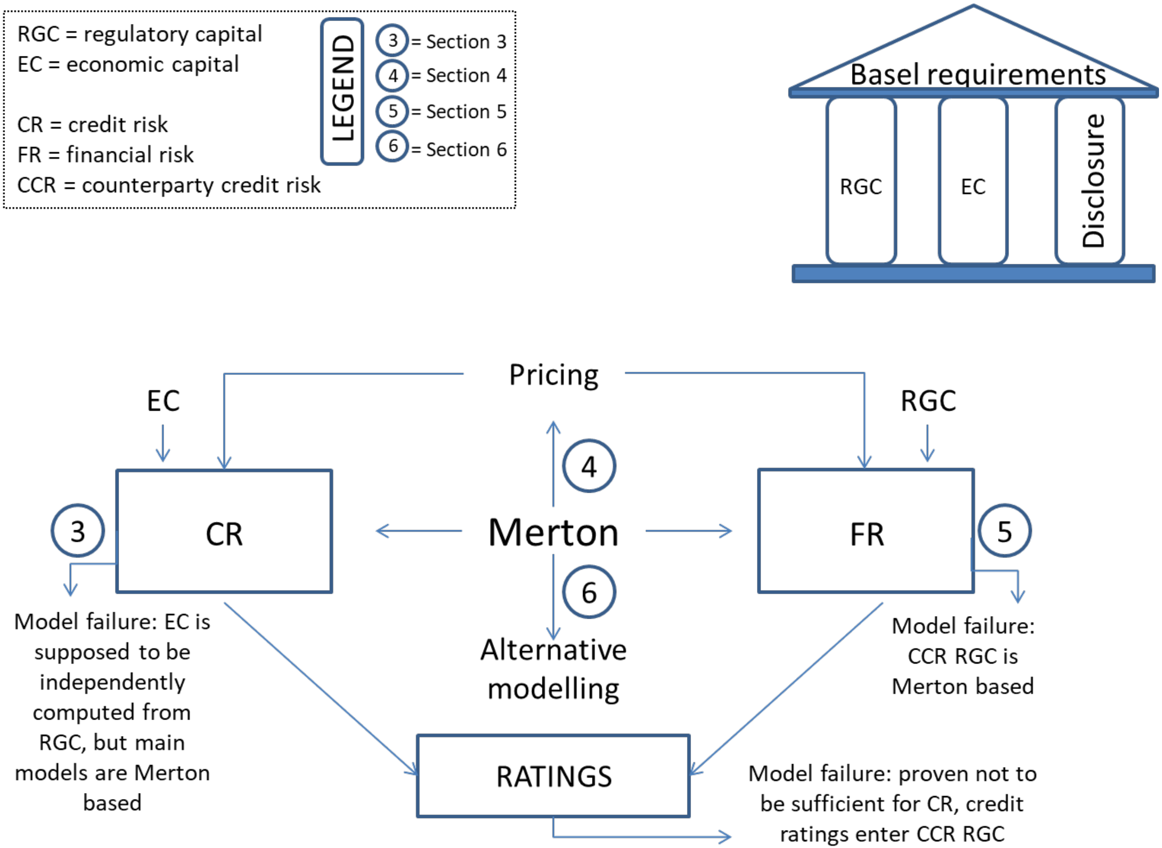
bility of transfer of an agent's economic distress via a financial asset, and systemic risk, defined *á la* Rochet and Tirole (1996) as the propagation of an agent's economic distress to other agents linked to that agent through financial transactions[8].

Previous literature expressed a sort of complementarity between the two of them, posing, however, a challenge to financial regulation. This is e.g. the finding of Nijskens and Wagner (2011). Back to the cause of the crisis of 2007-2009, they analyse various ways through which banks have transferred credit risk into the financial system: while banks may have shed their individual credit risk, they actually posed a greater systemic risk. Therefore, this systemic factor should represent a challenge for financial regulation, since regulation has typically focused on individual institutions. Analogous conclusion that Basel capital requirements are designed to limit each institution's risk seen in isolation, and they are not sufficiently focused on systemic risk is drawn by the recent paper Acharya et al. (2017). The systemic-risk component of their model is precisely correlated to a bank's expected losses during a crisis and to a financial firm's marginal expected shortfall, i.e., its losses in the tail of the aggregate sector's loss distribution, other than to its leverage. This result confirms the hypothesis of bias coming from the underlying models, which turns into a systematic effect. Although the systemic effects of financial dynamics are the object of much research, such as Freixas et al. (2000), Kreis and Leisen (2017), Aldasoro et al. (2017), mainly devoted to study the credit lines into interbank market as a propagator of system instability, so far no dynamics has been linked to what can be the source of this systemic instability, namely the financial risk generated by the common denominator of risk models. To test this hypothesis, we have first to proving that such possibility is concrete. The aim of this research chapter is precisely to analyse models correlation from a theoretical perspective, giving some mathematical hints to overcome superseded models. Future research could be devoted to prove this correlation in figures. We will see that a key point of financial models is how information is reflected in

[8]See e.g. Bonollo et al. (2014a) for a comprehensive overview on systemic risk.

the model; this includes the information that we know from the past, like credit ratings. Recent papers such as Ahnert and Georg (2017) and Aldasoro et al. (2017) link bank networks contagion and information; Hilscher and Wilson (2016) links credit risk and rating. Although this research addresses different facets of the same issue, none is able to relate all the features from a unique perspective. A recent banking directive on counterparty credit risk will allow linking together all the pieces of the puzzle that can connect credit risk to systemic risk, hopefully contributing to the enhancement of the underlying financial modelling. The following sessions will deal with topics apparently uncorrelated; actually, they all use the same structural form model for different kinds of risk assessment. A conceptual map is provided by figure 1.

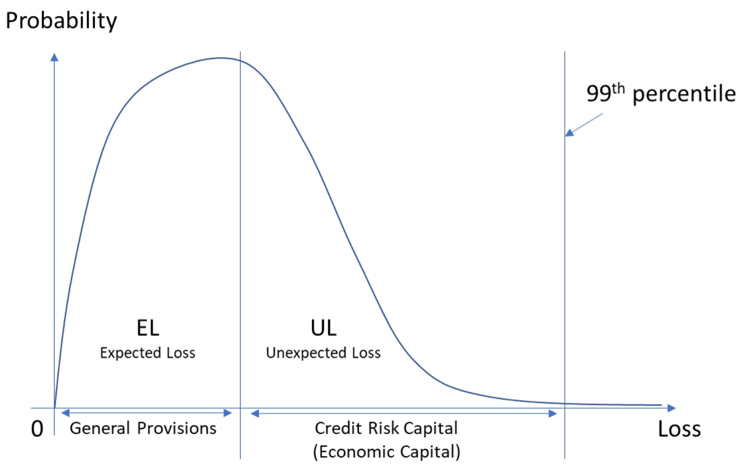
Figure 1: Conceptual map of the chapter



1.3 Models for assessing Economic Capital

Financial institutions need to have in place internal models for the assessment of the level of the overall capital buffer which is deemed sufficient to cover the risk of their business activities. Economic Capital is computed as follows: firstly a distribution of losses is inferred from the distribution of the portfolio. Decided a quantile, the average loss beyond the quantile or Expected Shortfall (ES) is computed, determining by difference the economic capital requirement[9].

Figure 2: Probability density function of credit losses as a percentage of total assets



Merton's methodology is vastly employed by the most common credit portfolio models for assessing economic capital requirements. Figure 3 shows a comparison of credit portfolio models for assessing economic capital. Among the four models, the most used are CreditMetrics and KMV PortfolioManager; both are based on Merton's formula. An underlying mathematical equivalence among these models has been demonstrated by Gordy (2000). From this substantial equivalence, we can infer that the

[9]On the contrary, Regulatory Capital is computed through the Value at Risk (VaR), that is the loss corresponding to a determined quantile. More precisely, the credit VaR at a confidence level q is the q-quantile of the loss distribution minus the Expected Loss (EL). The ES at confidence level q is the expected portfolio loss conditional on losses exceeding the q-quantile, minus the EL. See Ribarits et al. (2014).

vast majority of models that assess portfolio credit risk for economic capital is amenable to Merton's modelling. This is not a problem per se, but together with the fact that the economic capital calculations enter many usages (such as unexpected losses pricing proposals, setting of capital requirements, definition of the risk appetite framework of the bank, capital allocation and stress testing purposes) a model issue is envisaged if many other risks of a financial institution are assessed through the same methodology. The fact that Economic Capital should be independently assessed is not only a common best practice, but it is a Basel requirement. The Basel requirements, whose conceptual framework is detailed in section 1.5, constitute the three pillars that financial institutions have to ensue. Those pillars are the Regulatory Capital (RGC) and Economic Capital (EC) requirements, i.e. money to set aside for economic downturns, and disclosure requirements for transparency purposes. While regulatory capital requirements are the same for all banks, regardless of their size, focus or statute, economic capital requirements should express the internal view of the bank's portfolio losses. To this purpose, Economic Capital takes into account the bank's actual portfolio composition and characteristics in terms of concentration and diversification. While the regulatory view imposes rules-based calculation given by Basel III Pillar I standards, economic capital assesses credit risk through Monte–Carlo simulations. Although the different set up between RGC and EC let intend the different nature of the calculations and their aim to be independently assessed, the underlying Merton model is found to appear also in RGC calculations in section 1.5. To understand better how it is that possible, a preliminary knowledge of Merton's model is provided in section 1.4.

Figure 3: A comparison of main credit portfolio models

	Method of calculation	Underlying model	Credit Risk coverage	Default rates	Recovery rates	Factor Correlations
*CreditMetrics (JP Morgan/MSCI)**	simulations	Merton model	default + migration risk	historical data	beta distribution	proxied by stock data; sectors/industries
KMV PortfolioManager (Moodys)	simulations/ option theory	Merton model	default + migration risk	distance to default	beta distribution	proprietary methodology for extracting asset correlations
CreditRisk+ (CreditSuisse)	analytical	actuary model	default only	stochastic process (Gamma, Poisson)	Constant	one independent risk factor by sector
PortfolioView (McKinsey)	regressions/ simulations	econometric model	default + migration risk	econometric model	econometric model	correlation among macroeconomic time series

1.4 Merton's model

Since Merton's framework is so common, it is useful to get familiar with it. Some preliminary definitions are needed to understand the model at the core of our research chapter. A zero-coupon bond is a debt instrument issued for the purpose of raising capital. Who buys the bond (the bondholder) is loaning money to the issuer. The bond issuer pays back to the bondholder no coupon for interest but the entire payment (payoff) at the expiration date of the contract (maturity). Merton (1974) noted that a company's debt is analogous to a zero-coupon bond: if the firm asks for money to a bank, the bank becomes a bondholder and the payment to the debtholder at the expiration of the due debt corresponds to the payoff at maturity to the bondholder. Once liabilities are stochastically modelled, to make a comparison with the assets value Merton has to render the market value of the firm as a contingent claim V whose value depends on a stochastic process W and on time t. Then a firm's default process is driven by the evolution of the value of the company's assets: a default occurs when, at maturity T, the market value of the firm V is lower than its liabilities F. The principles of option pricing by Black and Scholes (1973) can be applied to model the financial evolution of a firm and give a simple formula for its insolvency risk. If the company were risk–free the lender would always get back the promised amount F at maturity. So the lender would be holding a risk free bond D. But companies are not risk free, there is a chance that they will not be able to repay the full amount F. If the company value V is less than F at maturity, the company will default, and the lender will take over the company, that can then be sold to recover what it was owed partially. So, if at maturity V is greater than F the lender loses 0 (no default) while if V is smaller than F the lender loses $F - V$. In a put option, the bondholder loses nothing if the underlying S is above the price at which the put option can be exercised (the strike price) K at maturity and $S - K$ otherwise. Therefore, the payoff to the debtholder is given by the sum of a safe claim payoff F plus the payoff of a put option with the value of the firm V as underlying and F the price at which the put option can be exercised (strike price).

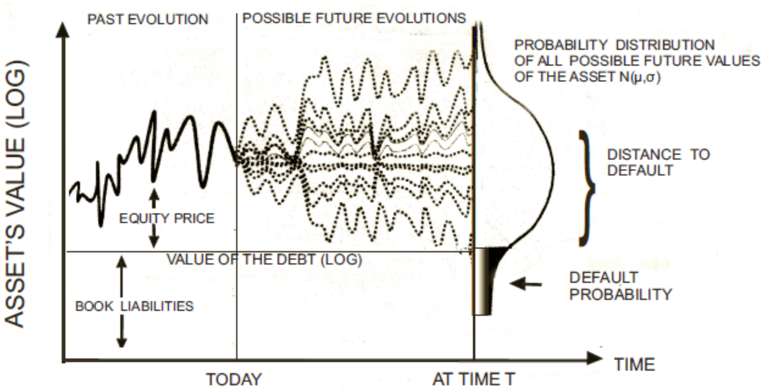
$$D_T = min\{F, V_T\} = F + min\{V_T F, 0\} = F - max\{F - V_T, 0\} \qquad (1.1)$$

Since the evolution of a firm's asset is driven by the value of the company's asset, the risk of a firm's default is linked to the variability of the firm's asset value. For quoted firms, a possibility of structural monitoring of the firm's value is represented by the observable share prices. From these data it is possible to estimate some useful parameters such as the assets instantaneous return and the volatility of return of firms' assets. It is, therefore, feasible to calibrate the theoretical model of geometric Brownian motion that has lognormal increments.

$$\frac{dV}{V} = \mu dt + \sigma_V(\varepsilon \sqrt{dt}) \tag{1.2}$$

V_t is the market value of the firm, dependent on time; μ is a parameter catching the assets instantaneous return; σ_V is the volatility measured by the standard deviation of the assets return.

Figure 4: Possible evolutions of assets value of firm



The credit risk is represented by the possibility that, at maturity T of the debt, the firm's asset value V_T is lower than the value of the loan repayment. The financial leverage of the firm is the horizontal line "value of the debt" $L = Fe^{-iT}/V$.

Since the debtholder's payoff is the sum of a safe claim payoff and a short position in a put option written on the firm's assets, the bond can be hedged by buying a put option on the value V_t of the firm's asset, with maturity equal to the maturity of the loan and strike price equal to the value of debt reimbursement. In this way, the combination of loan and purchase of put option gives as a result a guaranteed payoff equal to the amount of the loan F. The put option represents the loss given default. The equity holder, assumed to be the residual claimant, receives vice–versa the payoff of a call option:

$$E_T = max\{V_T - F, 0\} \tag{1.3}$$

such that $E_T + D_T = V_T$.

The risk-free equilibrium is achieved at time t when the synthetic price of put option and debt is risk–free: $P_t + D_t = Fe^{-i(T-t)}$ with discount factor i. The debt value is then computed as:

$$D_t = Fe^{-i(T-t)}N(d_2) + V_t N(d_1) \tag{1.4}$$

where N is the standard normal distribution function and

$$d_1 = \frac{(i + \frac{1}{2}\sigma_V^2)(T-t) + ln(V_t/F)}{\sigma_V \sqrt{T}} = d_2 + \sigma_V \sqrt{T-t}. \tag{1.5}$$

Consequently, formulas are derived for the default probability $PD = N(-d_2) = 1 - N(d_2)$ and the value D_0 of the loan, that increases with lower maturity of the loan T and lower financial leverage L.

$$D_0 = Fe^{-iT}\left[N(d_2) + \frac{1}{L}N(-d_1)\right]. \tag{1.6}$$

1.5 Regulatory requirements for counterparty credit risk

Counterparty credit risk measures the risk associated with derivative transactions. It differs from the traditional credit risk because of the bilateral risk profile (derivatives can be both asset or liability for different points in time) and the variation of the exposure depending on market and counterparty behavior (Usmen (1994) and Sayah (2016)). This section will study how Counterparty Credit Risk (CCR) is regulated at international level by the Bank for International Settlements (BIS). The Bank for International Settlements (BIS) is an international financial organization established in 19630 and owned by 60 member central banks, fostering discussion and issuing regulatory papers with the aim of promoting financial stability. BIS is organized into committees. The one deputed to banking supervision is the Basel Committee on Banking Supervision, the primary global standard setter for the prudential regulation of banks providing a forum for cooperation on banking supervisory matters. Its mandate is to strengthen the regulation, supervision, and practices of banks worldwide with the purpose of enhancing financial stability. Its advice is generally accepted and transposed into legal acts or directives by the recipient countries to implement a unified banking framework. The Standardised Approach for measuring Counterparty Credit Risk (SA-CCR) exposures Basel Committee on Banking Supervision (2014) contains the methodology proposed by BIS to tackle counterparty credit risk within the so–called Basel capital framework. The BIS document was issued in March 2014 and it is into effect since 1 January 2017. It replaces two old methodologies, namely the Current Exposure Method and the Standardised Method, with the aim of reducing the need for discretion by national authorities and limiting the use of banks' internal estimates. Whilst the aim is defensible in respect of a unified common regulatory system, the results of this study is that it is actually quite far from being achieved due to the use of superseded mathematical models, a reliance on CRAs assessment in some parts of the methodology, and to the implementation by individual banks within their internal models. Understanding how the SA-CCR methodology works and the model behind it, other than being interesting per se, prepares the pave for possible enhancements of the model behind such an important regulation.

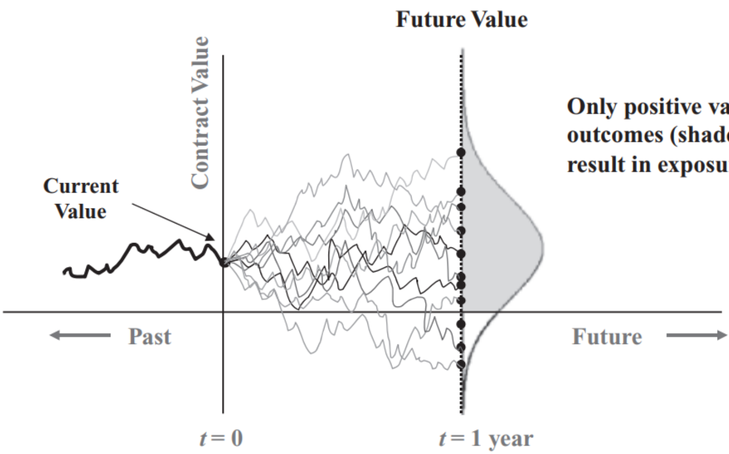
The SA-CCR will apply to over-the-counter derivatives, exchange-traded derivatives and long settlement transactions. The risky exposure or Exposure At Default (EAD) is calculated as proportional to the sum of two components, the amount that an entity would have to pay to replace an asset at present according to its current worth (Replacement Cost, RC) and a component that reflects the increases in exposure that could occur over time (Potential Future Exposure, PFE).

$$EAD = 1.4 * (RC + PFE) \tag{1.7}$$

The Replacement Cost (RC) represents a conservative estimate of the amount the bank would lose if the counterparty were to default immediately. More precisely, given a financial institution that has a portfolio of derivative contracts with a counterparty, its exposure to the counterparty at given future time is provided by the bank's economic loss in the event of the counterparty's default at that time. If the counterparty defaults, the bank must close out all its positions with the counterparty. To determine the loss arising from the counterparty's default, it is convenient to assume that the bank enters into an equivalent portfolio of trades with another counterparty in order to maintain its market position. Since the bank's market position is unchanged after replacing the trades, the loss is determined by the portfolio's replacement cost at the time of default. If V denotes the current mark–to–market value V and the counterparty were to default immediately, the loss for the bank would be equal to the greater of V and zero. If collateral is held against the derivative portfolio, its market value will determine a haircut whose amount C reflects the lender's perceived risk of loss from the asset falling in value or being sold in a fire sale. The Replacement Cost has then a formula exactly similar to the call option payoff for equity of Merton's model:

$$RC = max\{V - C, 0\}. \tag{1.8}$$

Figure 5: Possible evolutions of a derivative value



Contract Mark-to-Market Value and Stand-Alone Contract-Level Counterparty Credit Exposure. Source: Pykhtin et al. (2011).

In the same methodology, supervisory delta adjustments are parameters defined at the trade level and applied to the adjusted notional amounts to reflect the direction of the transaction and its non-linearity. For call and put options, they exactly recall the parameters d_1 and d_2 of the Merton formulas.

Supervisory parameters shown in figure 7 are instead based on subclasses of the asset class of the underlying. For the asset class *credit, single*

Figure 6: Merton's formulas applied to counterparty credit risk

δ_i	*Bought*	*Sold*
Call Options[13]	$+\Phi\left(\frac{\ln(P_i/K_i)+0.5*\sigma_i^2*T_i}{\sigma_i*\sqrt{T_i}}\right)$	$-\Phi\left(\frac{\ln(P_i/K_i)+0.5*\sigma_i^2*T_i}{\sigma_i*\sqrt{T_i}}\right)$
Put Options[7]	$-\Phi\left(-\frac{\ln(P_i/K_i)+0.5*\sigma_i^2*T_i}{\sigma_i*\sqrt{T_i}}\right)$	$+\Phi\left(-\frac{\ln(P_i/K_i)+0.5*\sigma_i^2*T_i}{\sigma_i*\sqrt{T_i}}\right)$
With the following parameters that banks must determine appropriately: P_i : Underlying price (spot, forward, average, etc) K_i : Strike price T_i : Latest contractual exercise date of the option The supervisory volatility σ_i of an option is specified on the basis of supervisory factor applicable to the trade.		

Source: Bank for International Settlement (BIS) (2014).

name (corresponding to credit default swaps) the subclasses differentiate following the rating classes. This classification appears to be innocent. However, it may contrast the objective of both the Financial Stability Board in U.S.A. and the European Commission to progressively lower the reliance on Credit Rating Agencies (CRAs) (see Financial Stability Board (2010) and EC (European Commission) (2014)). Indeed CRAs have the power to influence the stock markets; it is talked of "dictatorship of the analysts" since credit ratings enter both the markets by establishing a risk premium on the company, higher the riskiest the firm, and the regulatory framework when credit ratings help establishing calibrating parameters. It represents an externality to the regulatory framework, and financial institutions could face potential conflicts of interest. This chapter will skip a solution to the credit rating usage and focus on how to overcome the model's problem by proposing alternative ones. This is the content of section 1.6.

1.6 Reduced-form and partial information models

Structural-forms models like Merton's model rely on the assumption that every agent in the market can get the same level of disposable in-

Figure 7: Credit ratings in supervisory parameters for counterparty credit risk

Asset Class	Subclass		Supervisory factor	Correlation	Supervisory option volatility
Interest rate			**0.50%**	N/A	50%
Foreign exchange			**4.0%**	N/A	15%
Credit, Single Name	AAA		**0.38%**	50%	100%
	AA		**0.38%**	50%	100%
	A		**0.42%**	50%	100%
	BBB		**0.54%**	50%	100%
	BB		**1.06%**	50%	100%
	B		**1.6%**	50%	100%
	CCC		**6.0%**	50%	100%
Credit, Index	IG		**0.38%**	80%	80%
	SG		**1.06%**	80%	80%
Equity, Single Name			**32%**	50%	120%
Equity, Index			**20%**	80%	75%
Commodity	Electricity		**40%**	40%	150%
	Oil/Gas		**18%**	40%	70%
	Metals		**18%**	40%	70%
	Agricultural		**18%**	40%	70%
	Other		**18%**	40%	70%

Source: Bank for International Settlement (BIS) (2014).

formation. The mathematical device to represent information is called "filtration". More precisely, a filtration F is a family of sets F_t on a probability space Ω such that each set is contained into the next one. Sets F_t with $0 \leq t \leq T^*$ represent the level of disposable information at each point in time. The assumption of increasing sets means that agents do not lose information as time passes by. Sstructural-form models presume complete knowledge that means the whole filtration (information) underlying. If everything is known or predictable, then there is no room for chance. However, unpredictable events may still happen within this framework with serious economic effects. Reduced-form models have been introduced because, unless modelled through exogeneity simulation, not every default can be predicted. The mathematical framework beneath those models (intensity based model) is outlined.

On a probability space (Ω, P, P) consider two filtrations: F and G, defined over the same time interval $[0, T^*]$, one contained into the other:

$$G = (G_t)_{[0,T^*]} \subseteq F = (F_t)_{[0,T^*]}. \tag{1.9}$$

The default arrival is modelled by an aleatory time:

$$\tau_\delta : \Omega \to [0, +\infty] \tag{1.10}$$

that indicates a default arrival through a default indicator function (hazard rate):

$$H = I_{\{\tau_d \leq t\}}. \tag{1.11}$$

The hazard rate function is is a (F- G)-adapted stochastic process; this means that a market participant with access to partial market information G_t cannot observe whether default has occurred by time t ($\tau_d \leq t$) or not ($\tau_d > t$). Events in F_t are G_t-observable only when default has not happened until time t. At time t, the probability of a default before maturity T is the conditional expected value of the default indicator function at T given the partial filtration G_t: $PD(t) = E[H(T)|G_t]$.

Even if very versatile, intensity-based models are not convenient to stakeholders or well-informed private companies that know many things about a firm. A hybrid model between structural form and intensity models is provided by Duffie and Lando (2001). It is based on the assumption that not everyone has the same information regarding a firm's asset; the idea is once again to use different filtrations on the same probability space. This model allows a possibility of controlling the firm: the asset's value is represented by a stochastic process V. The "structural part" of the model consists of choosing an optimal liquidation policy until the condition "asset less than liabilities" hold: the choice is made by solving a Hamilton-Jacobi-Bellman equation. At the same time, the model accounts for an unpredictable default arrival, "controlled" by the partial filtration. The market sees the manager's information set plus a noise representing default as a surprise to the market, using filtering theory to go from the manager's information to the market's. An alternative approach is provided by Cetin et al. (2004). By contrast, in their reduced form model the market sees a reduction of the manager's information set. In both cases, the market's information set is the same as the manager's. The difference between the two models is that the perspective from filtering theory assumes additional noise while the point of view from reducing the manager's information set is that the manager knows less of it.

1.7 Conclusions

One should ask why modelling implementations are not often well reflected into the regulatory frameworks. In finance, more than in sociology, rules come after the mathematical or economic findings, but more often rules come after financial practices. This chapter revised two market practices that enter the regulatory framework for their easiness to be applied, although stemming from different assessments: credit ratings, retrieved from undisclosed algorithms by the Credit Rating Agencies, and models based on the normality assumption, derived from the literature on financial research. The importance of credit ratings should give speed and motivation to private or public Credit Rating Agencies to improve towards more efficient and accurate models of evaluation. At the same time, the regulator could continue relying on financial research and proposing its methodologies for regulatory capital requirements to financial institutions, but only if models are sufficiently updated to reflect all research contributions and developments. If, as it seems, the regulator prefers not to explore the latest research frontier but rather use steady methodologies, at least it should keep a critical eye on the same class of models driving several risk classes. Otherwise, the same model could fail in detecting all financial risks in favour of an increase of systemic risk factors. An immediate consequence is that stress testing is nomore a comparative tool to address upward and downward scenarios, but the only methodology to span the figures result. Future research may include: a theoretical review of other financial methodologies that are founded on the same set of assumptions; a quantitative assessment of the impact that common denominator practices have on risk management; a quantitative assessment of the impact that common denominator practices have on arbitrages; the studying of a measure that could be alternative to credit ratings. This chapter provides an alternative route to the classical mathematical modelling of incorporation by the stakeholders of information about insolvency cases. Much research has already been developed in this regard: a summary of the progress made by the research literature together with an analysis of pros and cons would also be desirable.

Chapter 2

Does corporate control matter to financial volatility?

2.1 Introduction

One relevant question, for financial stability purposes, regards the volatility and the shock transmission of financial markets. This is the phenomenon by which a stock market subject to a period of high volatility can cause the same instability to spread to other markets. On exchange-traded markets, the volatility of stock prices has been studied through many channels: none of them is related to the ownership structure of the firms issuing the shares, namely parent and affiliate firms, or stand-alone firms. Nonetheless, as stated by Altomonte and Rungi (2013), Multinational Enterprises (MNEs) contribute to a large portion of world-wide added value through the establishment of hierarchies of firms. Therefore, it is credible that there is a potential for multinationals to act as a channel for economic shocks, as intented by Desai and Foley (2006). To the best of our knowledge, what is missing in the literature is a bridge linking multinational companies and business groups to the share price volatility, if sucha a bridge does exist. With this study, we aim to fill the gap. We find that a connection exists, affiliates have a different behaviour on listed markets compared to their parent, and a business group behavior is well defined also on financial markets. We infer that the existence of such a relationship on financial markets discounts the investors credence that the business group internal strategy and information are passed quickly through the property channel, that goes beyond the nationalities of the companies constituting the business group.

Hierarchies of firms are groups made of a parent and its affiliates, which have a formally autonomous legal status. Among them, a corporate control linkage is established for the joint management of productive activities. Both a parent and some of its affiliates may quote some financial activities on stock exchanges. We study how such linkages may affect price volatility across firms that are part of the same hierarchy, possibly crossing national borders. This is particularly relevant in the case of multinational enterprises, when one or more affiliates are located in a country different from the country of the parent company. It is reasonable to assume that shocks occurring within a hierarchy of firms can be transmitted:

i. in the same country, across firms, when the group is domestic;

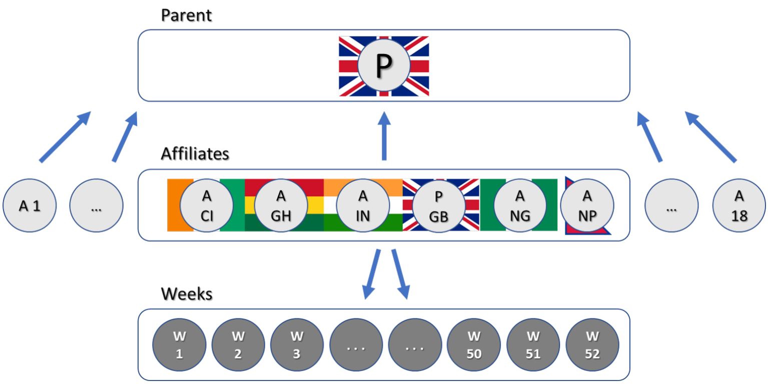
ii. across countries, across firms, when the group is multinational.

We find that corporate control matters. Affiliates reveal less volatility than their parent companies in weekly prices of financial activities quoted on the stock exchange. Moreover, after introducing an empirical three-level model for explaining observed variance, we find that there is less variance at a group level than across firms and time. That is, price activities show a narrower range of volatility when a hierarchy of firms is established. We argue that this is likely due to information on the common fundamentals that is passed to investors when they consider all the firms as a unique entity. In this framework, a shock occurring in one affiliate can pass to its co-affiliates faster, within one country in case of a domestic group, and across countries, in the case of MNEs.

Our findings are robust to different metrics of volatility and empirical methodologies. They point to a necessity to include control linkages when evaluating the prices of financial activities of firms belonging to the same corporate entity, albeit formally autonomous from a legal point of view. Take the case of Unilever PLC, located in U.K., with 281 subsidiaries and six branch locations recorded worldwide. Our dataset catches the parent company and five of its affiliates, issuing ordinary shares. Parent shares have GBP currency, while the listed affiliates, located in Ivory

Coast, Ghana, India, Nigeria, Nepal trade with XOF, GHS, INR, NGN, NPR currencies respectively. For each of them, as for the rest of firms of the dataset, we observe the share price of 52 weeks. It must be noted that those prices vary across both weeks and firms: we choose not to aggregate in any way the *a priori* variability stemming from the data, not to lose their informativeness.

Figure 8: Example: the hierarchical structure of Unilever PLC



The contribution proceeds as follows: in section 2.2 some related works are introduced. In section 2.3 the data are described. Some descriptive statistics, the construction of the financial covariates and the observed preliminary evidence are also provided. In section 2.4 the methodology is explained. In section 2.5 the empirical results can be found and section 2.6 concludes.

2.2 Literature review

Not many papers questions whether corporate control and business groups matter to financial markets. Restricting the focus on MNEs, one is Choi and Jiang (2009) relative to the smoothing role of operational hedging for the exchange risk. The authors find that MNEs, compared to propensity-score matched non-multinational enterprises, are less exposed to exchange risk and have higher stock returns, thanks to operational hedging. While this paper focuses on the side of business performance and risk, Aggarwal and Kyaw (2010) assess the positive role of the firm's multinationality on its capital structure: they find that multinational companies, compared to domestic companies, have significantly lower debt ratios, with such debt ratios decreasing with increasing multinationality. Keeping in mind that the static trade-off theory predicts an optimal capital structure of the firm (the debt/equity ratio that optimizes its value) the latter finding entails that either all MNEs have a different debt/equity target from domestic companies, or multinationality becomes a discriminant towards the preference for a pecking order theory rather than a static trade-off theory[1]: this could be indeed the case because of an asymmetry of information while acquiring external financing, evidenced by the structure of MNEs, between the inside and the outside group information available to investors. The question is now if this asymmetric information evidenced by MNEs does really depend on MNEs multinationality or if it depends just on its business structure. To this purpose, one could ask whether affiliates' multinationality facilitates corporate control: an evidence according to Sturgess (2016), global diversification premium is positively related to "winner-picking" transfers in internal capital market. For how it regards internal capital market, MNEs result to employ internal capital markets opportunistically to overcome imperfections in external capital markets according Desai et al. (2004) and Desai et al. (2005); Foley and Manova (2015) posits that financial frictions and the use of internal capital markets shape decisions that multinationals make regarding production locations, integration, and corporate governance. Desai et al. (2008) provides evidence that multinational affiliates also access parent equity when local firms are most constrained. This is the case also for domestic firms: Cai et al. (2016) empirical results on Chinese firms show that group affiliation decreases cash holdings, alleviating the agency costs due to free-cash-flow problem of undertaking low profitable investments[2]. A similar explanation for the use of subsidiaries and internal capital market is that firms use nonguaranteed subsidiary debt as a mean to control the wastage of free cash flows in their cash cows without inducing underinvestment in their growth divisions, according to Kolasinski (2009). Summing up, this literature seems to originate the necessity for a corporate control either from agency problems and informational asymmetry, or from financial frictions and imperfections in

[1] For a review on this topic, see Myers and Majluf (1984), De Haan and Hinloopen (2003), and Shyam-Sunder and Myers (1999).

[2] On agency costs and the free-cash-flow problem, see Jensen and Meckling (1976).

capital markets. Baker et al. (2003) provides a useful linkage between stock prices and the firm's need of external equity: they find that stock prices have a stronger impact on the investment of firms that need external equity to finance marginal investments. Gul et al. (2010) suggests that active trading enhances the incorporation of firm-specific information into stock prices, and Gârleanu et al. (2015) states that the market is subject to contagion: an adverse shock to investors in some locations affects prices everywhere, because small changes in market-access costs can cause a change in the type of equilibrium, leading to discontinuous price changes. From a macroeconomic perspective, not only there is no strong evidence that group-level firms are better insured against times of adverse macroeconomic shocks (see Khanna and Yafeh (2005)), but full integration of global financial markets may be not very desirable for financial stability, as risks were spread around the world: even if financial globalization provides a reduction in transaction costs and boosts both trade and foreign direct investment, the price is in terms of more exposure of the real economy to financial shocks; international linkages can propagate economic shocks and rise the default probabilities of firms from different areas (see Stiglitz (2010), Poelhekke (2016) and Al-Haschimi et al. (2014) respectively). Increased connectivity among firms plays a role in financial stability: Desai and Foley (2006) claim is that "multinationals act as a channel of economic shocks: high correlations of country-wide returns and investment within multinational firms suggest that shocks that occur in one part of the world may be transmitted across borders because of a multinational firm's world-wide network of subsidiaries". Eden (2017) shows that financial integration amplifies shocks in relatively distorted economies; Cravino and Levchenko (2016) assessed a non-negligible impact of foreign shocks on productivity shocks, transmitted by all foreign multinationals combined; Di Giovanni and Levchenko (2009) study the mechanisms through which output volatility (the volatility of aggregate output growth) is related to trade openness, with sectors more open to international trade being more volatile. So, even if business groups have been studied from both a micro and a macroeconomic perspective, there are still some open questions such as: do markets and investor recognize that it exists a group-level financial volatility? Are business groups trying to minimize their financial volatility using their subsidiaries? Vice versa are increasing business groups becoming themselves sources of financial instability, by bringing more connections into the world-wide financial system?

2.3 Data construction and preliminary evidence

The dataset can be broadly described as consisting of two main components: a static and a time-dependent part. The parent-affiliates dataset includes all financial information of parent, affiliates and stand-alone companies; it is relative to the year 2013 and retrieved from Orbis. The 52-weeks addendum sourced from Bloomberg links the firm's share prices to each firm with its kit of corporate information. A parent company is a firm that owns more than 50% equity of another company, the "affiliate", in respect to which it will become the "parent". An affiliate is thus a firm having at least (and exactly) one parent company. In our dataset only listed firms are included: all non-listed affiliates of the parent companies are excluded from the dataset. The set of all affiliate with their uniquely defined parent is what we call a business group. A stand-alone firm is a company with no parent. The world-wide dataset that takes into account the volatility measure consists of 43'374 firms: 26'644 parent, 2'638 affiliates and 14'092 stand-alone[3] firms. The average number of affiliates per parent is 1.88, with peaks of 64 and 131 affiliates per parent at the 95% and at the 99% frequency percentile respectively. Table 1 shows the regional distribution of firms into the dataset split by parent, affiliate, and stand-alone firms. The most populated regions of the final dataset are the U.S.A., the E.U., and China, followed by Asiatic and Indian regions, Japan and Canada. The number of affiliates is relevant even though less than parent companies.

It could be the case of financial volatility being dependent on the firm structure main indicators rather than the business structure of the group. We assess the dependence of volatility from several financial variables of the firms that account for the firm's structure, productivity, financial leverage, and credit constraint. We construct four indicators: *financial assets* and *fixed assets* retrieved from the *Asset* side and *equity/debt* and *long/short* term debt from the *Liability* side of the balance sheet. *Financial assets* approximates the relevance of financial activity *vis à vis* the productive activity. This ratio provides a control for financial share price volatility by revealing the percentage of financial expenditure in financial investments over the characteristic activity of the firm. The percentage *fixed assets* of total assets monitors the investment decisions as a way to improve productivity. The inverse of the leverage ratio *equity/debt* is in-

[3]See data appendix A for details on the data and on the financial variables constructed.

Table 1: Geographic coverage by type of firm

Region	Affiliates	Parent	Stand-alone	Total
Africa	97	431	143	671
Asia - other	418	1'965	2'031	4'414
Canada	191	1'835	1'057	3'083
Central America	76	630	197	903
China	158	3'536	907	4'601
Europe - EU	526	5'260	1'825	7'611
Europe - Non EU	27	348	32	407
India	177	1'024	2'570	3'771
Japan	262	2'654	551	3'467
Korea	86	658	987	1'731
Middle East	232	1'083	917	2'232
Oceania	43	1'338	243	1'624
Russia	69	121	24	214
South America	146	325	139	610
USA	130	5'436	2'469	8'035
Total	2'638	26'644	14'092	43'374

The most populated regions of the final dataset are the U.S.A., the E.U., and China, followed by Asiatic and Indian regions, Japan and Canada. The number of affiliates is relevant even though less than parent companies.

tended to capture a premium of not recurring to external funding and at the same time it can reveal the health status of the firm, since highly indebted or less capitalized firms are likely to be less resilient during crisis time. The maturity composition of financial sources reflected by long term debt over short term debt ratio provides an insight into the financing choice of the firm: e.g., a high amount of short term debt compared to long term debt may indicate suffering financing needs. We consider also the indicators of *labour productivity* and *financial pressure*. The latter, defined similarly to the borrowing ratio of Nickell and Nicolitsas (1999), is used to assess the premium on borrowing costs and the probability of credit being rationed. In the post-estimation of section 2.5.3, we use the *Tobin's q* to assess the dependence of the estimated parameter for the parent on its investment opportunities.

Volatility is defined as the logrange between maximum and minimum price in a fixed amount of time; for the purposes of this article, that amount of time corresponds to a week. The measure defines a dispersion of the price fluctuations around the traded stock price; the exact definition of volatility is reminded to formula 2.4 of section 2.4.1. Volatility values are negative and in line with the results of mean estimation of Alizadeh et al. (2002) that they obtain via Monte Carlo simulation.

Figure 9 plots the volatility values for Unilever PLC and its affiliates and helps depicting what we are going to assess. In blue, we can distinguish the behaviour of the parent company over one year. It seems clearly to represent a trend for its affiliates, even though the latter show a more widespread volatility. If every parent company with its affiliates were like this case, the chart would tell the following:

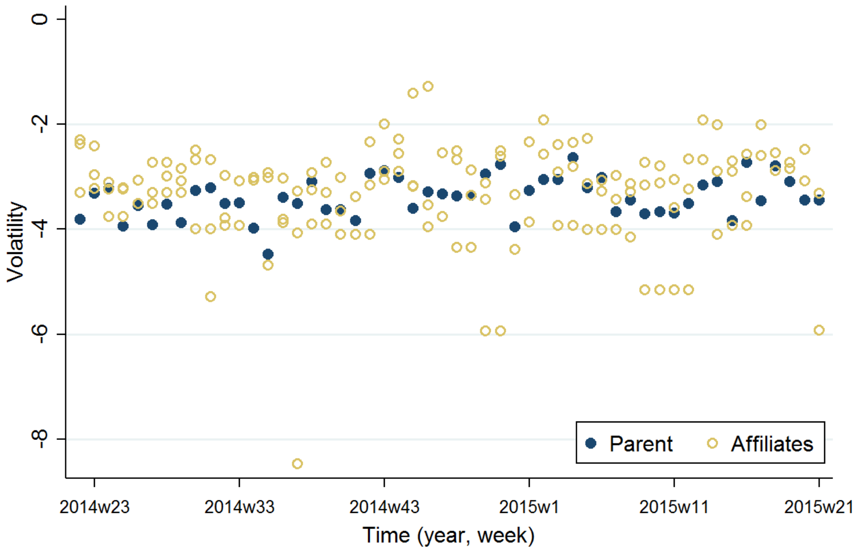
1. the business group listed affiliates show a group behaviour in terms of volatility, of which the parent seems to dictate the trend;

2. the affiliates behaviour is clearly discernible from the parent one and adds variability;

3. the group structure does not decompose or disappear through the weeks, even though some outliers.

The first item postulates the existence of a group-level decision taking able to influence investors on the stock markets. This is likely due to information on the common fundamentals that reaches investors considering the business group as a unique entity. Also, this could reveal

Figure 9: Volatility of Unilever PLC and its listed affiliates



The behaviour of the parent company (blue) and its affiliates (amber) over one year. The parent seems to dictate a trend to its affiliates.

unnoticed sources of systemic risk, when the property channel acts as a chain for the propagation of instability on financial markets. In terms of methodology and expected results, the observations translate into the following hypotheses:

1. a multilevel random model is preferable to OLS since there is a considerable overlap of volatility among a business group;

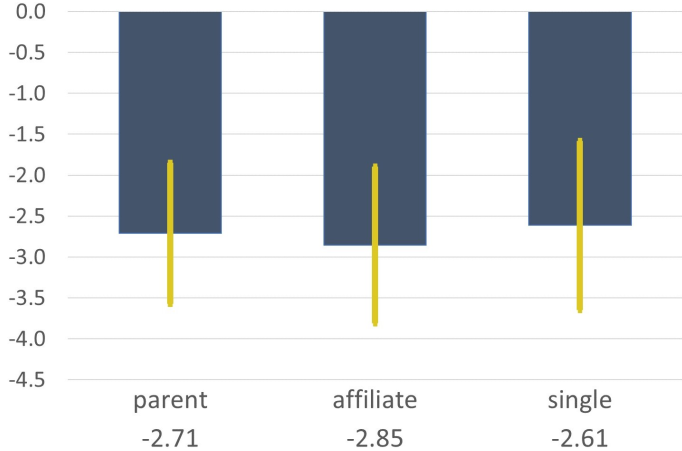
2. a dummy for affiliate should be significant and with an higher dispersion compared to the one of the parent company;

3. the snowflake structure depicted by figure 8 is robust across the weeks, that is the standard deviation coefficients from the multilevel regression are expected to be significant.

Figure 10 displays mean values and standard deviations by type of firm[4]. Listed affiliate firms are slightly less volatile compared to their

[4]Other descriptive tables can be found in the appendix.

Figure 10: Volatility (mean and standard deviation) by type of firm



Listed affiliate firms are slightly less volatile compared to their parent.

parent. The expected negative premium to volatility by the dummy affiliate is confirmed in table 2, both on the parent and affiliate dataset only and by regressing on the whole dataset. In absolute terms, the premium further increases once we standardize the measure of volatility and we control for cluster on the population of firm identifiers (id). The preliminary evidence suggests that the parent and affiliates show distinguishable volatility behaviours, even with the same common trend. This could signal a strategy of the parent company to build a hierarchy of firms to stabilize its volatility on financial markets, thanks e.g. to different trade currencies.

2.4 Methodology

The methodology applied can be easily split into two main modellings: the mathematical framework for the definition of financial volatility and the econometric model for the build-up of the results.

Table 2: Preliminary evidence, excluding and including single firms

Dependent variable: Volatility	Parent and affiliates	All firms
Affiliate	-0.155***	-0.189***
	(0.003)	(0.003)
Constant	-0.023***	0.011***
	(0.001)	(0.001)
R squared	0.002	0.002
N	1′281′413	1′841′890

* p< 0.050, ** p< 0.010, *** p< 0.001, standard error in parentheses. Standardized variables, clustered by firm. The dummy for affiliates is significant and shows a negative premium to volatility.

2.4.1 The measure of volatility

We use a stochastic model for financial volatility based on stock prices. Following Alizadeh et al. (2002), we apply a first-order parametrization to a stochastic volatility model, in which the price S of a security evolves as a diffusion process[5] with both instantaneous drift μ and volatility σ dependent on a latent diffusion process ν with constant volatility β and no correlation between the Wiener processes of the price and the latent variable equation:

$$\begin{aligned} dS_t &= \mu(S_t, \nu_t)dt + \sigma(S_t, \nu_t)dW_{S_t} \\ d\nu_t &= \alpha(S_t, \nu_t)dt + \beta(S_t, \nu_t)dW_{\nu_t} \end{aligned} \tag{2.1}$$

[5]A diffusion process is a Markov process, i.e. a random process whose future probabilities are determined by its most recent values, such that, under several regularity assumptions, is completely determined from its first two moments. See Itô (1974) for its mathematical definition.

where:

$$\begin{cases} dW_{S_t} dW_{\nu_t} = 0 \\ \sigma(S_t, \nu_t) = \sigma_t S_t \\ \sigma_t = exp(\nu_t) \\ \alpha(S_t, \nu_t) = \alpha(ln\overline{\sigma} - ln\sigma_t) \\ \mu(S_t, \nu_t) = \mu S_t \\ \beta(S_t, \nu_t) = \beta. \end{cases} \tag{2.2}$$

By combining equations 2.1 and 2.2, we have that returns dS/S follow a geometric Brownian motion:

$$\begin{aligned} \frac{dS_t}{S_t} &= \mu dt + \sigma dW_{S_t} \\ dln\ \sigma_t &= \alpha(ln\overline{\sigma} - ln\sigma_t)dt + \beta dW_{\nu_t}, \end{aligned} \tag{2.3}$$

and therefore, by Itô's lemma, the log security price process $s_t = ln\ S_t$ follows a Brownian motion. Alizadeh et al. (2002) prove that the univariate range, defined as the interval between the maximum and the minimum log stock price over a period, is an efficient volatility estimator, nearly log-normal, and robust to market microstructure noise induced e.g. by the bid-ask bounce. The latter can cause an overestimation of the measured price volatility that is increased instead by the transactions bouncing between buy and sell[6]. Therefore, in case we had chosen the *realized volatility* instead of a range-based estimator, the realized volatility could have accumulated a large bias by summing up upward biased squared returns, since it is the sum of squared returns over a given sampling period[7]. Thanks to the result of Alizadeh et al. (2002) we build the weekly volatility proxy[8] as:

$$vol_t = ln(high_t - low_t), \tag{2.4}$$

where $high_t$ and low_t represent the observed weekly high and low

[6]On market microstructure noise, see e.g. Bandi and Russell (2008), Bandi and Russell (2006).

[7]For further estimation of stock volatility with range-based estimators, historical evolution and comparison with other methods, see e.g. Christensen and Podolskij (2007) Jacob et al. (2008), Martens and Van Dijk (2007), Christensen and Podolskij (2007).

[8]The equation 2.4 referring to observed prices is also dependent on the index i for each firm in the population; we omit this subscript for simplicity, minding however the important dependence.

prices respectively of the process of log prices s_t[9]. Notice that this dispersion measure does not depend on the series of opening nor closing prices, thus it is independent across weeks, since it is function of non-overlapping increments of a Brownian motion.[10]

Our methodology will not proceed further by aggregating this measure across weeks. Although several price-based estimators can serve well as standard deviation volatility measures (see e.g. Martens and Van Dijk (2007)), the benefit of our approach consists in a very low mathematical manipulation of the data: since we do not calculate any aggregated measure across the weeks, we are able to translate time variability genuinely into the model. That reduces some numerical noises, but comes at a price: the econometric model able to reflect the longitudinal-nested dataset is one-level more complex than it would be by using an aggregate measure for volatility across weeks, and it is described below.

2.4.2 The econometric model

Our strategy is to exploit Maximum Likelihood Estimation (MLE) - based multilevel models, that should be compared to the Ordinary Least Square (OLS) regression. Multilevel or random-effects models allow for the most accurate estimation of the regression parameter when there are several layers inside a variable. Hierarchical, nested or time–dependent dataset would generally require such an approach to avoid unpleasant fallacies that lead to estimation biases, such as interpreting associations at the higher level as pertaining to the lower level. Instead of having to make a decision regarding the unit of analysis, the use of multi–level modeling will avoid the fallacies by considering all levels simoultaneously. All the cases in which we have clusters among the data are better studied through this kind of methodology: any within–cluster dependence violates the assumption of ordinary regression models and consequently ordinary regression produces incorrect standard errors. Furthermore, multi–level models represent the only way to assess an intra–layer dependence. In our case the main layers are the population of firms and the parent companies on top of them. We will adopt both the two–level in the case of

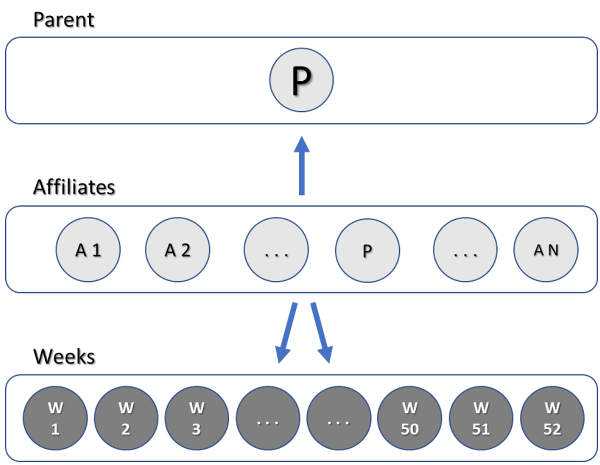
[9] Both the $sup_{t=weekj}s_t$ and the $inf_{t=weekj}s_t$ are realized into the $high_t$ and low_t respectively, in every closed interval represented by weeks $j = 1, 2, ..52$.

[10] E.g., given the series of opening log prices $open_t$, $H_t = ln(\frac{high_t}{open_t})$, $L_t = ln(\frac{low_t}{open_t})$, $ln(H_t - L_t) = ln(\frac{high_t}{open_t} * (\frac{open_t}{low_t}) = ln(high_t - low_t)$.

volatility measure aggregated over time and the three–level model when using our definition of volatility whose value changes over time[11].

The intuition that we want to test is whether belonging to the same business group creates a discrimination at a group level among the population of affiliate companies. This group specific bias will be determined by a group common pattern through, e.g., vertical integration, knowledge sharing, internal capital markets, group management decisions. We use a three-level random intercept model instead of a two-level model in order to keep the time variable for the reasons exposed in the previous paragraph. The most granular level is given indeed by the time-variable financial volatility. A middle level is represented by the whole population of firms and it is nested into the upper level of parent companies. Therefore, our model has both a longitudinal design between first two levels and a cross-sectional or hierarchical design between parent and affiliates. An example scheme is given in figure 11. It fully reflects the preliminary snowflake structure evidenced by the example in figure 8.

Figure 11: Nested and longitudinal structure of the three-level model



The three-level model in the base case takes the following form:

[11] A comprehensive review of multilevel models is provided in Gelman and Hill (2006).

$$y_{tij} = \beta_1 + \varsigma_{ij}^{(2)} + \varsigma_{j}^{(3)} + \epsilon_{tij}. \qquad (2.5)$$

The run can estimate the financial volatility y_{tij} among the weeks $t = 1, 2, ..52$ and the zero means and mutually uncorrelated error components. In our representation:

- the random intercept $\varsigma_{j}^{(3)}$ for parent group j has variance that represents the *between groups* portion of variance;
- the random intercept $\varsigma_{ij}^{(2)}$ for affiliate i and parent group j has variance that represents the *between affiliates and within groups* portion of variance; and
- the residual error ϵ_{tij} for week t, affiliate i and parent group j has variance that represents the *between weeks, within affiliates, and within groups* portion of variance.

We will estimate the model (2.5) with several covariates x_{ij}. In the case we have only the dummy for affiliate x_i equal to 1 if the company is an affiliate company and 0 otherwise the formula is:

$$y_{tij} = \beta_1 + \beta_2 x_{ij} + \varsigma_{ij}^{(2)} + \varsigma_{j}^{(3)} + \epsilon_{tij}. \qquad (2.6)$$

The estimation results by layers will tell if the three-level well captures the time varying dependency of the volatility against the business group structure, without soiling the volatility itself with *a priori* data manipulations imposed by a synthesized mathematical object. The business group structure itself will be also recognized if we obtain significant standard deviations at firm and group levels. In this case corporate control will translate into a well-defined hierarchical object able to play a role for the price volatility propagation.

2.4.3 The design of the robustness checks

We perform the robustness checks with the most common aggregated measures for standard deviation of the log prices over the weeks[12]. The rationale is that we do not want to choose a specific measure to test against our model. Since no measure has been classified as the best one

[12]Specifically, we refer to estimators tested by Martens and Van Dijk (2007).

by the literature, we make a comparison with many measures to see whether any of them shows an opposite behaviour or results are in line among the measure and against ours. If the three-level model depicted by formula (2.5) served respectively for time, population of firms, and business groups represented by the parents, once we aggregate over time we must drop the time in weeks level and use a two-level model below for the remaining nested part:

$$y_{ij} = \beta + \varsigma_j^{(3)} + \epsilon_{ij}. \tag{2.7}$$

Several volatility measures are estimated at two-level random intercept regressions. Specifically, given the process of log prices s_t[13], and its observed weekly opening prices $open_t$, closing prices $close_t$, high prices $high_t$ and low prices low_t, and defined the squared return as $r_t^2 = (close_t - close_{t-1})^2$, we test the two-level model against:

i. the standard deviation of the "old" variable *Volatility*;

ii. the *realized variance* =

$$\Sigma_{t=1}^{52} r_t^2; \tag{2.8}$$

iii. the *realized range*[14]=

$$\frac{1}{4ln2}\Sigma_{t=1}^{52}(high_t - low_t)^2; \tag{2.9}$$

iv. the *Garman-Klass* estimator[15] =

$$\Sigma_{t=1}^{52}\left[0.5(high_t - low_t)^2 - (2ln2 - 1)(close_t - close_{t-1})^2\right]; \tag{2.10}$$

v. the *Rogers-Satchell* estimator[16] =

$$\Sigma_{t=1}^{52}[(high_t - close_t)(high_t - close_{t-1}) + (low_t - close_t)(low_t - close_{t-1})]. \tag{2.11}$$

[13]The same observation of 8 applies here and in all the following formulas.

[14]The realized range is based on Parkinson (1980) estimator = $\frac{(high_t - low_t)^2}{4ln2}$.

[15]For further reference, see Garman and Klass (1980).

[16]This estimator has the merit of being unbiased whatever the drift μ. For further reference, see Rogers and Satchell (1991).

2.5 Empirical findings

2.5.1 OLS regressions

Robust OLS regressions without and with financial covariates confirm the preliminary evidence by showing a negative and significant premium to volatility from the affiliates in all regressions. Both standard regression (table 3) and controlling for country and sector (table 6) show no relevant impact on volatility except for the percentage *fixed assets*. The negative dependence found suggests that firms with a higher percentage of investments are less volatile on financial markets. When controlling on the total population of firms, the impact of the financing structure becomes significant and positively correlated to volatility. This signals that the financing time-structure of the firm matters when no business group is identified and firms are standing-alone. No role seem to play labour productivity and financial pressure. The coefficient of the capital structure equity/debt becomes slightly significant when controlling for country and sector fixed effects (see table 6) and positively correlated to volatility. Firms therefore face some form of credit market imperfections in violation of Modigliani and Miller (1958), and the ones with higher equity are less volatile. In the same table 6 the positive coefficient of long term over short term debt indicates that firms preferring short term borrowing are likely to have lower stock price volatility, probably because of a higher default risk or difficulties in getting longer debt financing. No relevant difference in all regression is found instead when inserting time fixed effects.

Table 3: OLS regressions, excluding (P&A) and including single firms (All)

Dependent variable: Volatility	P&A	All	P&A	All	P&A	All
Affiliate	-0.155***	-0.189***	-0.085***	-0.125***	-0.077***	-0.110***
	(0.015)	(0.015)	(0.022)	(0.022)	(0.025)	(0.025)
Labour productivity			-0.021	-0.026*	-0.012	-0.015
			(0.012)	(0.013)	(0.010)	(0.011)
Financial pressure			0.002	-0.001	-0.001	-0.002
			(0.003)	(0.003)	(0.004)	(0.005)
Financial assets					-0.267	-0.310
					(0.578)	(0.536)
Fixed assets					-0.047***	-0.061***
					(0.011)	(0.009)
Equity / debt					-0.005	-0.003
					(0.006)	(0.006)
Long / short debt					0.084	0.058***
					(0.054)	(0.009)
Constant	-0.023***	0.011***	-0.088***	-0.047***	-0.119***	-0.080***
	(0.004)	(0.004)	(0.007)	(0.007)	(0.012)	(0.011)
R squared	0.002	0.002	0.001	0.002	0.003	0.005
N	1’281’413	1’841’890	324’367	406’751	258’830	311’014

* p< 0.050, ** p< 0.010, *** p< 0.001, standard error in parentheses. Standardized variables, clustered by firm. A negative and significant premium to volatility from the affiliates is shown in all regressions. No relevant impact on volatility from the other regressors except for the percentage *fixed assets*.

2.5.2 Random-effect regressions

The results of the three-level random intercept regression are shown by table 4. They confirm the OLS results of coefficients sign and significance representing a double-check one of the other. The random-intercept model however is able to show the relative intra-dependence within each business group that the OLS cannot assess, and the low p-values of the Wald chi square statistics indicate the goodness of fit of the overall three-level model. The novel evidence of the existence of a financial management of a business group is well-defined according to the significance of the standard deviation coefficients. The volatility among weeks shows not surprisingly the highest variability, and the standard deviation between affiliates is generally higher than between business groups. While controlling for financial variables, we find that labour productivity becomes weakly significant despite the financial volatility. While making the full regression, financial variables are found to be weakly significant or not significant except again for *fixed assets*. The behaviour of Unilever PLC is representative of the behaviour of all business group in the dataset; all the hypotheses of section 2.4.2 are verified. The strong significance of the standard deviation coefficients confirms a solid snowflake hierarchical structure and provides evidence for a well defined financial group-level actor in volatility transmission mechanisms of financial markets, the reason of which we date back to the information on the group-level fundamentals that is available to investors.

2.5.3 Group level sources of volatility

Financial volatility is possibly driven by hidden aspects of parent firms affecting the whole business group. Indeed, after the three-level model we are left with an an unexplained source of variability that already discounts the control put in the estimate. It is given by the intercept $\varsigma_j^{(3)}$ common to every affiliate belonging to the same parent and it represents the volatility component that is group-specific. We can assess with a prediction the group-level random intercept, obtaining a fixed parameter, slightly negative, for all the affiliates population. We can exploit another advantage of the random-intercept model given by the possibility of inspecting a source of variability lying *outside* of the tested model: the existence of this source of variability indicates that belonging to a group or another makes a difference. A representation of the random-intercept at group level *Parent* and its prediction is given in figure 12.

Table 4: Random intercept regressions

Dependent variable: Volatility			
Affiliate	-0.087***	-0.035	-0.056*
Labour productivity		-0.026**	-0.013
Financial pressure		0.002	0.002
Financial assets			0.129
Fixed assets			-0.042***
Equity / debt			-0.006
Long / short debt			0.050
Constant	0.069***	-0.047***	-0.083***
SD (bw. groups)	0.558***	0.451***	0.465***
SD (bw. affiliates)	0.604***	0.490***	0.423***
SD (bw. weeks)	0.626***	0.641***	0.630***
N parent	26’720	6’760	5’344
N affiliate	29’282	7’236	5’676
N of weeks	52	52	52
N of observations	1’281’413	324’367	258’830
Log likelihood	-1279623.4	-329578.7	-258105.1
Wald chi2(2)	24.9	11.3	21.4
Prob>chi2	0.0001	0.0104	0.0033

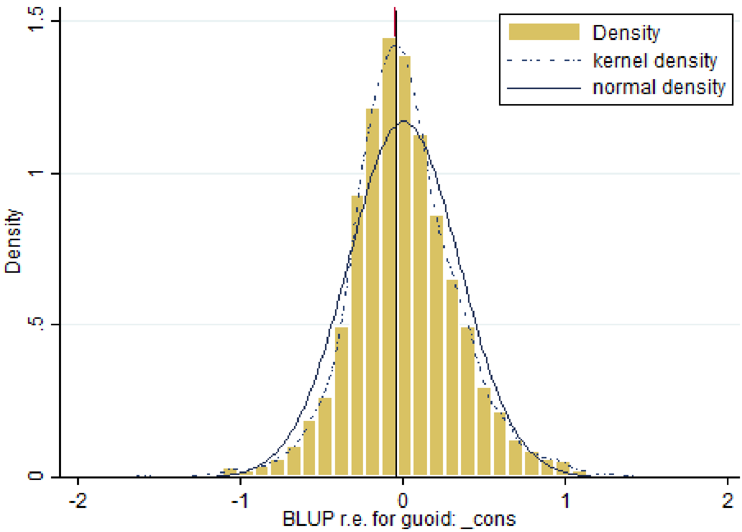
* $p < 0.050$, ** $p < 0.010$, *** $p < 0.001$. Random–effect model confirms OLS results. Financial variables are found to be weakly significant or not significant except again for *fixed assets*. The strong significance of the standard deviation coefficients confirms a solid hierarchical structure across time.

Table 5: Group-level sources of volatility

Dependent variable: Parent			
Size	-0.135***	-0.137***	-0.141***
	(0.001)	(0.001)	(0.001)
N countries		0.739***	0.816***
		(0.055)	(0.055)
N sectors		-0.017	-0.017
		(0.017)	(0.017)
Tobin's q			-0.178***
			(0.017)
Constant	0.041***	0.713***	0.783***
	(0.001)	(0.048)	(0.048)
R squared	0.109	0.109	0.115
N	265'928	265'928	254'800

* $p< 0.050$, ** $p< 0.010$, *** $p< 0.001$, standard error in parentheses. Standardized variables, robust. Size, Tobin's q and numbers of countries in which the parent has affiliates show significant coefficients; therefore they are correlated to the group–level volatility.

Figure 12: Graphical representation of the random-intercept at group level



Then we perform a post-estimation regression by testing, for each parent or group[17], some parent-related measures such as size, number of countries in which the group has affiliates, number of sector of product diversification and Tobin's q. The OLS regression takes as dependent variable the estimate of the group-level random intercept. Results in table 5 show that size, Tobin's q and numbers of countries in which the parent has affiliates show significant coefficients. While the firm's size and marketability impacts seem to lower volatility, the group variability is increased with dispersion across many countries. Firm size is expected to be positively correlated with the probability that firms attract external finance under the pecking order theory[18]; therefore, it is reasonable that its share market will be more liquid and therefore the group variability decreases with size. The market value of the firm over replacement costs

[17] Parent firms balance sheet are consolidated in most of the cases. However, the confusion between parent and group has not to be considered by an accounting perspective, that would be misleading because of lack of harmonized accounting reporting, but rather the group must be intended as per our modelling definition.

[18] According to De Haan and Hinloopen (2003).

has the same effect of the firm's size of decreasing the negative value of *Parent*. The impact of sector diversification is not significant.

2.5.4 The results of the robustness check

The econometric methodology outlined in section 2.4.3 is interesting *per se*; for how far the study is conceived, it represents also a robustness check. We provide the results of estimation through alternative measures of volatility starting from the closest ones to our volatility measure: the standard deviation of *Volatility* and the *realized range*. Left-hand panel of table 7 shows the behaviour of the OLS results obtained by collapsing the volatility measure over the weeks with the standard deviation operator. We can observe that the magnitude orders between the dummy affiliate effect over the two datasets without and with single firms is the same as in the three-level model: the effect is higher on the largest dataset. Vice versa the effect is higher on the smallest dataset for the realized range (right-hand panel of table 7) and for the other measures of section 2.4.3 (see the Appendix, table 10). Table 9 shows comparison values for the regression results on the dataset without single firms. All the results reveal a coefficient of the dummy affiliate still negative and strongly significant. Tables 8 and 11 show the results of the two-level model. We see that the behaviour of the alternative measures of volatility is completely in line with the results of section 2.5.2 and the standard deviations are statistically strongly significant for all the measures.

2.6 Concluding remarks

We ask whether Multinational Enterprises (MNEs) and, more in general, business conglomerates have an influence on the volatility of financial markets stock prices. While the answer can be intuitively thought as positive, it is necessary to assess what does a financial management of a business group means in case it is well defined. To answer the research question, we build a world-wide dataset of weekly stock prices of quoted firms linked by a parent-affiliate relationship. We develop a methodology to assess whether listed firms show a group behaviour and if there is any relevant difference between parent and affiliates in terms of volatility, and whether the supposed group structure does not decompose through the weeks. If the parent-affiliate relationship has an influence over share prices volatility it can consequently act as a channel for the propagation of financial shocks or imbalances on the financial markets. We find that the parent-affiliate relationship is significantly correlated to financial markets volatility and a hierarchical two-layer model exists on top of the retrieved financial data. The empirical investigation confirms the hypotheses and does not depend on the empirical model chosen. Even adding corporate regressors commonly used to investigate firms structure, productivity and constraints, the business group structure keeps significant over the weeks. We can conclude that corporate control has an impact on financial volatility. The findings provide a robust definition of business group acting on financial markets and open the pave for the investigation of new dynamics through the undiscovered channel of corporate control. The methodology built can be easily generalized to vertically multi-layered hierarchical structures; in particular the same methodology could be used to investigate multi-layered business groups in which affiliates are parent firms themselves.

Appendix A.

Additional information on the data

The initial dataset consists of a 154 countries dataset, with a total of 63'737 firms, of which 30'550 parent, 3'664 affiliate, 29'523 single companies. Europe, Asia, India, Korea and South America are the regions where we find more stand-alone companies than parent firms; in all the other regions world-wide, we register more companies with at least one affiliate than single firms.

The financial variables described in section 2.3 are computed at firm level as follows.

- *Size* is proxied by the year sales;
- *Financial assets* is the share of financial assets (other fixed assets plus cash equivalent) over total assets excluding other fixed assets and cash equivalent;
- *Fixed assets* is the percentage of fixed assets over total assets;
- *Equity/debt* is the ratio between shareholders' funds and long term debt;
- *Long/short debt* is the ratio between non-current and current liabilities;
- *Labour productivity* is the value added per employee;
- *Financial pressure* is given by interest payments over the profit before tax plus depreciation;
- *Tobin's q* is computed as the firm market valuation over the accountable value of fixed assets; precisely, it is computed as 1 plus the marginal market value of the firm minus its book value.

Figure 13: Volatility densities by region

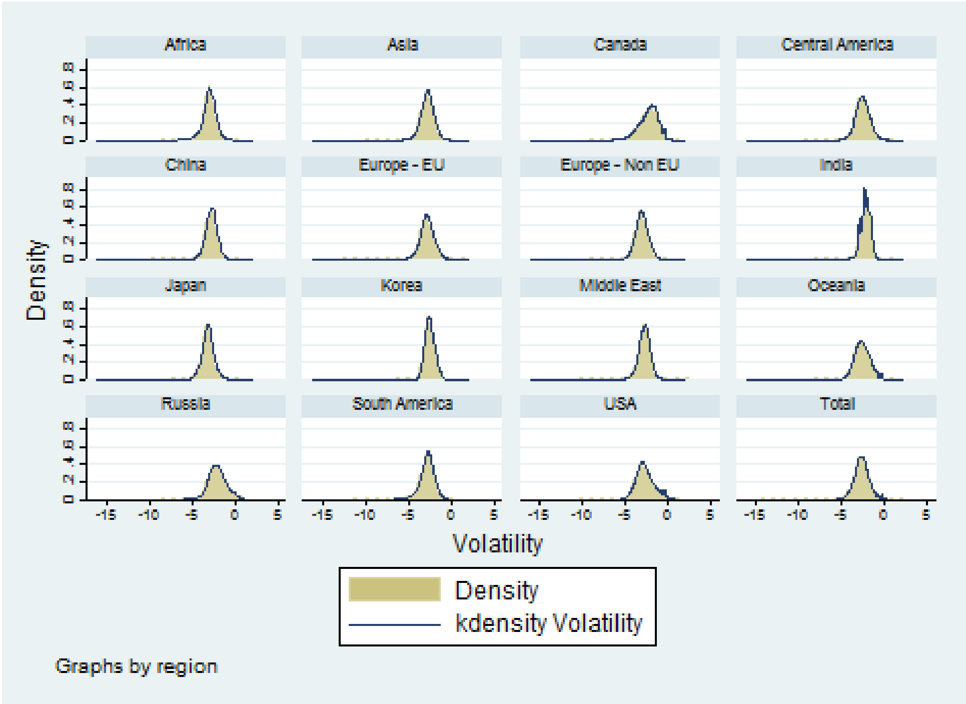
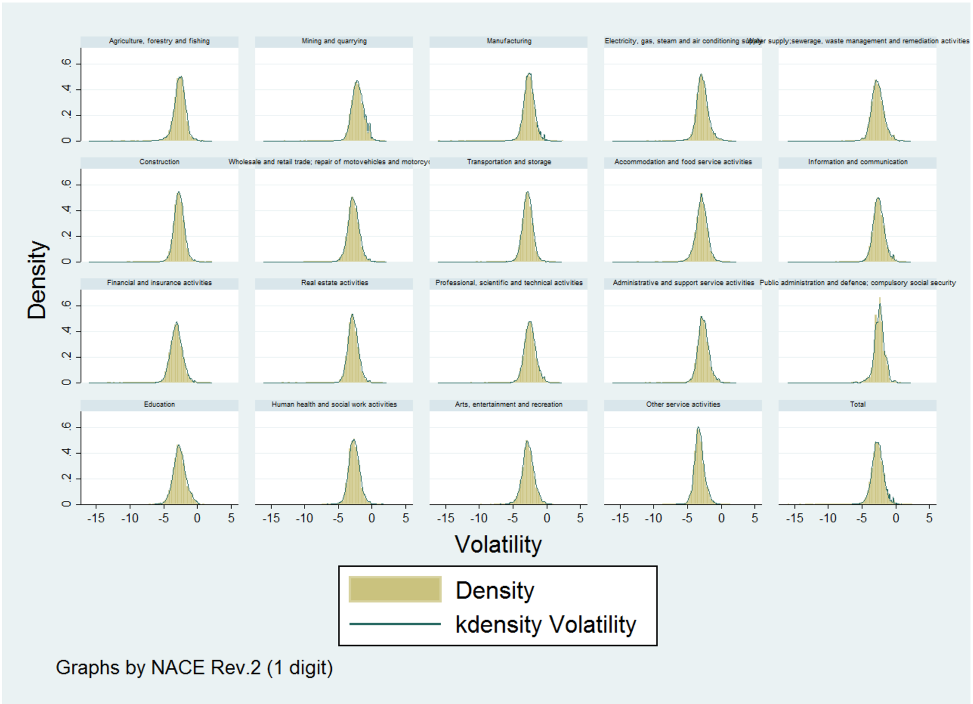


Figure 14: Volatility densities by sector



Appendix B.

Additional tables

Table 6: Regression with country-sector control, excluding (P&A) and including single firms (All)

Dependent variable: Volatility	P&A	All	P&A	All	P&A	All
Affiliate	-0.126***	-0.148***	-0.105***	-0.135***	-0.100***	-0.123***
	(0.013)	(0.012)	(0.021)	(0.020)	(0.022)	(0.022)
Labour productivity			-0.015	-0.019*	-0.008	-0.009
			(0.008)	(0.009)	(0.006)	(0.007)
Financial pressure			-0.003	-0.004	-0.006	-0.007
			(0.003)	(0.003)	(0.005)	(0.005)
Financial activity					-0.207	-0.393
					(0.528)	(0.488)
Fixed assets					-0.050***	-0.055***
					(0.011)	(0.010)
Equity / debt					-0.009*	-0.008*
					(0.004)	(0.004)
Long / short debt					0.083*	0.051***
					(0.040)	(0.009)
Constant	-0.025***	0.019***	-0.086***	-0.047***	-0.116***	-0.083***
	(0.003)	(0.003)	(0.006)	(0.005)	(0.010)	(0.009)
R squared	0.211	0.230	0.164	0.154	0.163	0.156
N	1’274’315	1’809’773	323’707	405’441	258’425	310’214

* p< 0.050, ** p< 0.010, *** p< 0.001, standard error in parenthesis. Standardized variables, clustered by firm.

Table 7: Robustness check results, standard deviation of volatility and realized range

Dependent variable:	SD(Volatility)		Realized range	
	P&A	All	P&A	All
Affiliate	-0.090***	-0.136***	-0.249***	-0.088***
	(0.016)	(0.016)	(0.016)	(0.016)
Constant	-0.038***	0.008	0.166***	0.005
	(0.006)	(0.005)	(0.005)	(0.004)
R squared	0.001	0.001	0.006	0.001
N	29’696	44’446	34’214	63’737

* p< 0.050, ** p< 0.010, *** p< 0.001, standard error in parentheses.

Table 8: Two-level robustness check results for standard deviation of volatility and realized range

Dependent variable:	SD(Volatility)			Realized range		
Affiliate	-0.009	-0.013	-0.007	-0.250***	-0.116***	-0.081***
Labour productivity		-0.176*	-0.006		-0.015	-0.004
Financial pressure		0.001	0.001		0.001	0.003
Financial assets			0.064			0.013
Fixed assets			-0.022*			-0.030**
Equity / debt			0.001			0.004
Long / short debt			0.058			0.128*
Constant	-0.038***	-0.165***	-0.210***	0.166***	0.079***	0.047**
SD (bw. groups)	0.611***	0.398***	0.464***	0.379***	0.438***	0.517***
SD (bw. affiliates)	0.672***	0.526***	0.273***	0.870***	0.587***	0.363***
N parent	27'084	6'760	5'340	30'602	7'486	5'857
N affiliate	29'696	7'242	5'672	34'214	8'063	6'237
Log likelihood	-38883.2	-7222.5	-4387.9	-46672.2	-8878.8	-5860.5
Wald chi2(2)	0.2	4.6	7.7	186.2	20.9	23.3
Prob>chi2	0.6344	0.2025	0.3595	0.0001	0.0001	0.0002

* p< 0.050, ** p< 0.010, *** p< 0.001.

Table 9: Robustness check results, other measures of volatility

Dependent variable:	Realized variance	Garman-Klass	Rogers-Satchell
Affiliate	-0.226***	-0.238***	-0.193***
	(0.015)	(0.017)	(0.017)
Constant	0.157***	0.161***	0.130***
	(0.006)	(0.005)	(0.005)
R squared	0.005	0.006	0.004
N	34’214	33’281	33’858

* p< 0.050, ** p< 0.010, *** p< 0.001, standard error in parentheses.

Table 10: Robustness check results including stand-alone firms, other measures of volatility

Dependent variable:	Realized variance	Garman-Klass	Rogers-Satchell
Affiliate	-0.074***	-0.081***	-0.067***
	(0.015)	(0.016)	(0.016)
Constant	0.004	0.005	0.004
	(0.004)	(0.004)	(0.004)
R squared	0.001	0.001	0.001
N	63’737	61’704	62’964

* p< 0.050, ** p< 0.010, *** p< 0.001, standard error in parenthesis.

Table 11: Two-level robustness check results, other measures of volatility

Dependent variable:	Realized variance	Garman-Klass	Rogers-Satchell
Affiliate	-0.153***	-0.243***	-0.211***
Constant	0.157***	0.161***	0.130***
SD (bw. groups)	0.607***	0.326***	0.316***
SD (bw. affiliates)	0.755***	0.889***	0.891***
N parent	30’602	29’860	30’320
N affiliate	34’214	33’281	33’858
Log likelihood	-47012.2	-43536.5	-46103.1
Wald chi2(2)	70.7	174.7	135.8
Prob>chi2	0.0001	0.0001	0.0001

* p< 0.050, ** p< 0.010, *** p< 0.001.

Chapter 3

Assessing Financial Distress dependencies in OTC Markets: a New approach using Trade Repositories data

3.1 Introduction

The 2007–2008 financial crisis was mostly caused by liquidity and credit (counterparty) risks within the banking system. Although liquidity and Over-The-Counter (OTC) derivatives were the main causes of distress, one of the most surprising effects was contagion of other financial players and other markets and sectors. This fact motivated the introduction of *systemic risk* as a new *building block* in regulatory frameworks, such as the Basel III (see, e.g., Bank of International Settlement (BIS), 2013);

Financial Stability Board (FSB), 2015). Financial instability and systemic risk assessment are attracting increasing interest among researchers and regulators, and many different approaches and techniques have been proposed.[1] For example, recent literature on financial systems[2] focuses on payments system, interbanking deposit markets, and OTC derivatives markets. However, the latter is one of the most difficult to investigate due to the complexity of the "underlying" transactions, that is, the derivatives' payoffs with their highly customized structures, and the scarce availability of detailed data, especially in the past. Aggregated statistics on OTC derivatives markets are usually released by international organizations such as BIS (Bank for International Settlement) and OCC (U.S. Office of Comptroller of the Currency), or banking associations such as ISDA (International Securities and Derivatives Association). However, the collapse of 2007–2008 stressed the need for better data in order to assess systemic risk and prevent market abuse. Therefore, changes in regulatory frameworks mandated a more detailed description of deals, thus revealing a more representative and current picture of derivatives markets (see, e.g., Duffie et al., 2010; Russo, 2010). In the United States, prior to the Dodd-Frank Act (U.S. 111th Congress, 2010), financial institutions had fewer obligations regarding the amount of financial leverage, counterparty risk exposure, market share, and other data that had to be reported to any regulatory agency. Now, however, new rules require information on OTC exposure and assign to specific agencies the role of collecting and sharing data. Similarly, in Europe the creation of the European Securities and Markets Authority (ESMA) and the European Systemic Risk Board (ESRB) was motivated by the need to enforce the provision of data to improve supervision and restraint of systemic risk (EC (European Commission) (2013); EC (European Commission) (2013)). In addition, the European Parliament established the European Market Infrastructure Regulation (EMIR) with Regulation No. 648/2012 (EUP (European Union Parliament) (2012)). Both the EMIR in Europe and the Dodd-Frank Act in the United States aim to provide a more detailed description of derivatives markets. Although only authorities are allowed to exploit the highest level of granularity, market players also can benefit from this flow of data through trade repository services (TRs), which collect and match data and allow the public access to this information.[3] In

[1] We omit review of this strand of literature, referring the interested reader to Bisias et al. (2012) and Brunnermeier (2016) and the references therein for a detailed analysis of financial stability measures and models used for assessing systemic risk.

[2] For instance, a useful review on the application of network theory tools and methodologies can be found in Upper (2011).

[3] For a detailed description of trade repository activities, see, e.g., DTCC (Depository Trust & Clearing Corporation) (2013, 2014).

Europe, this results in an intermediate level where data are aggregated according to, for example, different asset classes and maturity features, while in the United States, transaction data are reported almost in real time and it is only confidential data that are not available.[4] Thus there is an increasing need for transparency. In this regard, for OTC derivatives and central counterparties, useful analyses can be found in Cecchetti et al. (2009) and Hull (2014), while for interest rate derivatives markets, some insights can be found in Avellaneda and Cont (2010) and Fleming et al. (2012).

In this chapter we describe how segments of the OTC derivatives market are related to each other. In particular, we focus on reciprocal co-movements during distressed market conditions using a novel database on OTC transactions that is based on trade repositories data. To study how sub-markets are mutually influenced we deal with the following issues. First, we identify a suitable set of OTC sub-markets within the IRS instruments by aggregating deals according to financial and contractual terms. Unfortunately, identification of a robust sub–market concept is not straightforward. Along with several financial drivers that provide support for clustering the whole market, we face some technical problems, such as the availability and the quality of a wide set of data for different financial instruments. We confine our analysis to the most common type of IRS contracts, that is, *fix-to-floating* instruments, considering deals where the underlying rate is *USD-LIBOR-BBA*, the contractual start is *Spot*, and the currency is the *U.S. dollar*. This represents the most significant subset in our dataset (which is supplied by IASON ltd[5]). The identification of sub-markets is then driven by the *maturity* of the contract, the *frequencies* of the swap legs and the presence of *clearing* agreements. Second, we construct an indicator for assessing the level of distress present in these sub-markets. This distress indicator combines several dimensions useful for measuring market conditions, such as proxies for the bid-ask spread of prices, their volatility, the number of deals, and the average traded volumes. Basically, although we are aware that market distress might be related to a wide set interacting factors, we focus on a simple and intuitive

[4]For a deeper study on the divergences between the European Union and the Unites States in financial market regulations, see, e.g., Acharya et al. (2010), Lannoo (2013), and Valiante (2010); a valuable reference for better understanding the key requirements involved in the aggregation of TRs data is provided by FSB (2014).

[5]Iason ltd is a consulting firm operating in risk management tools and applications. For references, see *http://www.iasonltd.com/*.

framework that synthesizes the main forces affecting market dynamics. Therefore, the aim of this indicator is to reflect some of the most evident and relevant dimensions that influence the ordinary course of business within OTC sub-markets. Third, we analyse the distress dependence between pairs of sub-markets by means of the copula theory and we investigate the joint distribution of the increments of the distress indicator. Copula functions provide mathematical instruments for modeling multivariate stochastic dependence structures that are able to capture various forms of stochastic dependence, not only linear dependencies. In particular, we estimate the Kendall's tau correlation coefficients and the joint upper-tail probabilities (henceforth, joint probabilities of distress). Our approach is similar to the one introduced in the IMF Banking Stability Measure report by Segoviano and Goodhart (2009) to describe the distress interdependent structure among financial institutions. However, our context of application is completely different and, therefore, we face technical issues that are specific to our case study (e.g., we do not have "default" thresholds and so the methodology used in Segoviano and Goodhart (2009) is not feasible in our case).

Although our approach exploits standard methods used in risk management, to the best of our knowledge the present work is one of the first empirical studies based on micro-founded trade repository data. Related literature includes, for example, Slive et al. (2012), who analyse central clearing effects in Credit Default Swap (CDS) markets through the Intercontinental Exchange (ICE) Trust and Clear Europe data, and Markose et al. (2012), who investigate the role of systemically important financial institutions (SIFIs) within the U.S. CDS market using Federal Deposit Insurance Corporation (FDIC) data. A very recent paper that exploits data from the Depository Trust and Clearing Corporation (DTCC) is Gehde-Trapp et al. (2015); however, it focuses on CDS rather than on IRS. A comparison between official BIS statistics and detailed trade repositories data is made in Bonollo et al. (2015), who describe how OTC derivatives market segmentation can be implemented through the provision of more granular flows of information related to the new regulatory framework. The novelties of our analysis are both the originality of the dataset that we exploit to identify specific sub-markets and the distress indicator that we introduce. We note that despite the several difficulties to be faced due to the pioneering nature of our work (e.g., the quality of the TRs data, sub-market identification, and the new distress indicator definition), our outcomes are consistent with practical intuition. While using a micro-prudential approach to analyse the portfolio and risks of a bank is a complex, albeit sharply focused, task, inferring from global market data the risks of a portfolio comprised of the entire financial system is a new frontier in the research. In the past, lack of detailed data and the lack of an agreed upon definition of systemic risk (see, e.g., IMF, BIS, FSB (2009); FSB (Financial Stability Board), 2010; Bonollo et al., 2014b) made very challenging the measurement of distress signals arising from financial markets. This work aims to introduce into the debate on systemic risk assessment and financial stability a way to exploit trade repositories data so as to detect distress and crisis phenomena.

The chapter is organized as follows: after a detailed description of the dataset and the procedure employed for sub-markets identification (section 3.2), we introduce the indicator used to investigate distress dependencies among sub-markets (section 3.3). Then, section 3.4 explains in detail the methodology that we use to estimate co-dependencies. Finally, the results of our analysis are illustrated and discussed in section 3.5. Section 3.6 concludes and makes some suggestions for future lines of research.

3.2 Description of the dataset

International statistics on OTC markets are usually provided by several organizations, such as BIS and OCC, or by banking associations, such as ISDA. These statistics are based on some reporting dealers, for example the biggest (a few dozens) commercial and investment banks, that regularly send some low granular data on their own derivatives deals to these central organizations, which, in turn, publish the information after having applied data cleaning procedures to avoid, for example, double counting issues. Although this flow of data covers a high percentage of the global OTC markets, the information related to both asset classes and payoffs is not very detailed and may be not comparable among different data providers. For instance, mark-to-market consensus prices may differ from pre-trade indicative prices and from the actual trade prices at which derivatives are exchanged. For these reasons, we rely on a trade repository dataset retrieved from *GTRAnalytics*,[6] which collects

[6] This is a software developed by the consulting firm IASON Ltd. For references, see *http://www.financial-machineries.com/gtr-analytics.htm*

trade information from several trade repositories and for many types of instruments, controlling for obvious inconsistencies and mismatches. The latter process limits potential biases due to data misreporting and the fragmentation that may arise from merging datasets from different sources and across many regulations.

Our study focuses on the interest rates derivatives market, which, at the end of December 2014, accounted for 80% and 75% of the global OTC derivatives market in terms of the outstanding notional amount and the gross market value, respectively. In particular, that the swaps market was worth $381 trillion compared with $505 trillion of the total outstanding notional amount of the interest rate market[7] motivates our choice to study the swaps segments as a representative case study for the global OTC derivatives market. In particular, for each deal (identified by an ID) our database specifies the asset class of the instrument and reports a set of information about contractual terms, including, for instance, time of execution, effective date and contractual expiry of the deal, the settlement and the currencies of both underlying assets, payment frequencies, day count convention, and the notional and the price. In addition, we also exploit information on clearing agreements and collateral positions, which enriches the description of market trends and improves risk assessment. We refer to prices and volumes of actual traded deals in the market, which extends the traditional use of *offered* rates (bid/ask quotes shown by brokers or data providers) and *consensus* (quotes/prices submitted by market contributors) data.

3.2.1 Sub-markets identification

Identifying a robust sub-market concept is not straightforward. Along with several financial drivers that provide support for clustering the whole market, we must take into account some technical issues, such as the availability and the quality of a wide set of data for different financial instruments. However, although the methodology we propose is somewhat heuristic, we believe that at this first stage of the study this is a reasonable approach to analysing co-movements in OTC sub-markets.

[7] Data refer to BIS statistics and to single currency contracts only. For further references, see *http://www.bis.org/statistics/derstats.htm*.

To ensure comparability, we restrict our analysis to *fix-to-floating* instruments. For the same reason, we consider contracts where the underlying rate is *USD-LIBOR-BBA*, the contractual start is *Spot*, and currency is *U.S. dollar*. This represents the most significant subset in our dataset. Specifically, the identification of sub-markets is driven by the *maturity* of the contract, the *frequencies* of the swap legs, and the presence of *clearing* agreements. Data investigation suggests considering fix-to-floating instruments with leg frequencies equal to *(3m vs. 3m)* and *(6m vs. 3m)*. In addition, we aggregate deals according to three main maturities: less or equal to 2 years (*Short*), between 2 years and 10 years (*Medium*), and greater or equal to 10 years (*Long*). Finally, we distinguish between contracts for which there are clearing agreements (*C*) and those for which uncleared (*UC*) conditions are present (see table 12).

Table 12: Sub-markets definition

Sub-mkt	Fix-to-Floating	Maturity	Clearing
1	*(3m vs 3m)*	*Short*	*C*
2	*(3m vs 3m)*	*Medium*	*C*
3	*(3m vs 3m)*	*Long*	*C*
4	*(6m vs 3m)*	*Short*	*C*
5	*(6m vs 3m)*	*Medium*	*C*
6	*(6m vs 3m)*	*Long*	*C*
7	*(6m vs 3m)*	*Short*	*UC*
8	*(6m vs 3m)*	*Medium*	*UC*
9	*(6m vs 3m)*	*Long*	*UC*

Fix-to-Floating refers to contracts with swap legs frequencies equal to *(3m vs 3m)* or *(6m vs 3m)*. *Short*, *Medium*, and *Long* refer to deals with maturities less than or equal to 2 years (*Short*), between 2 years and 10 years (*Medium*), and greater or equal to 10 years (*Long*). Finally, data are further partitioned according to the presence (*C*) or absence (*UC*) of clearing agreements.

The frequency of leg payments became a relevant factor after the financial crisis, when it became clear that the frequency of cash flows changed both the liquidity (funding) risk and the counterparty risk for the two involved financial agents. This is known as the *multiple curve new framework*.[8] In other words, one cannot evaluate financial instruments

[8] See Pallavicini and Brigo (2013).

without considering the frequency of cash flows since, *ceteris paribus*, the IRS fair values will be slightly different. The netting flag is also a very informative variable. For instance, both the Dodd-Frank Act and the ESMA regulation require financial institutions to employ netting agreements in transaction management so as to keep credit exposures as low as possible. In addition, even enterprises are required to follow this practice for deals above some relevant threshold (e.g., 3 bn Euro in terms of outstanding notional for interest rate derivatives in the ESMA regulation). For this reason, we assume that the Yes/No clearing agreement digit can be used as a proxy for counterparty class, that is, financial institutions vs. enterprises.

Although information on traded deals is available for the first part of 2013, for the following analysis we consider only data from *September 2013* to *April 2015* since the number of reported deals at the beginning of 2013 is not satisfactory. This choice ensures a good availability of data throughout the reference period. Table 13 sets out descriptive statistics for each sub-market.[9]

[9] We further check for double counting in the transactions by controlling for contractual terms. In particular, we consider as duplicated deals those transactions that are equal in terms of dissemination ID, contractual expiry, effective date, end date, price, and notional amount.

Table 13: Number of deals and volumes for each sub-market

IRS (3m x 3m)

	Short		*Medium*		*Long*		***Total***	
	Cleared	*Uncleared*	*Cleared*	*Uncleared*	*Cleared*	*Uncleared*	***Cleared***	***Uncleared***
Number of deals	1,170	154	9,028	706	9,406	133	**19,604**	**993**
Notional amount	175,226	8,359	874,483	34,479	412,779	4,131	**1,462,488**	**46,969**

IRS (6m x 3m)

	Short		*Medium*		*Long*		***Total***	
	Cleared	*Uncleared*	*Cleared*	*Uncleared*	*Cleared*	*Uncleared*	***Cleared***	***Uncleared***
Number of deals	14,063	2,128	100,555	9,547	92,008	9,405	**206,626**	**21,080**
Notional amount	2,301,060	294,994	9,258,744	745,467	4,134,122	396,999	**15,693,926**	**1,437,460**

Descriptive statistics refer to the number of deals and their notional amounts (in millions of U.S. dollars) from September 2013 to April 2015. The upper part shows data for contracts with swap leg frequencies equal to *(3m vs. 3m)*; the lower part shows deals with swap leg frequencies equal to *(6m vs. 3m)*. *Short*, *Medium*, and *Long* refer to deals with maturities less than or equal to 2 years (*Short*), between 2 years and 10 years (*Medium*), and greater or equal to 10 years (*Long*). Finally, data are further partitioned according to the presence (*C*) or absence (*UC*) of clearing agreements. The totals for each combination (i.e. the statistics for each sub-market) are shown in bold.

Results suggest that deals involving *fix-to-floating* instruments with leg frequencies equal to (6m vs. 3m) are more frequent than those with leg frequencies equal to (3m vs. 3m). This is more evident once we consider deals characterized by clearing agreements. In particular, short maturities are less diffused, while figures are comparable for the *Medium* and the *Long* sub-sets. To identify sub-markets, these descriptive statistics suggest discarding, due to data limitations, uncleared deals of *fix-to-floating* instruments with leg frequencies equal to (3m vs. 3m). Therefore, our final list of sub-markets is comprised of six sub-sets with leg frequencies equal to (6m vs. 3m) and three sub-sets with leg frequencies equal to (3m vs. 3m), the latter characterized by the presence of clearing agreements.

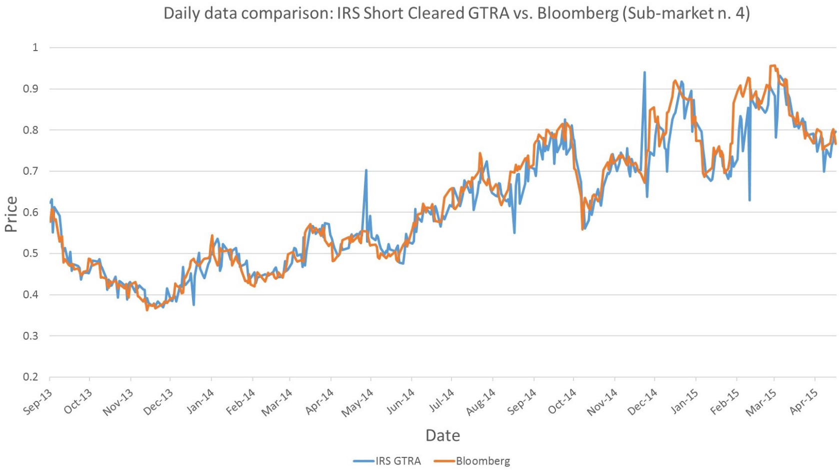
3.2.2 Comparisons with other data sources

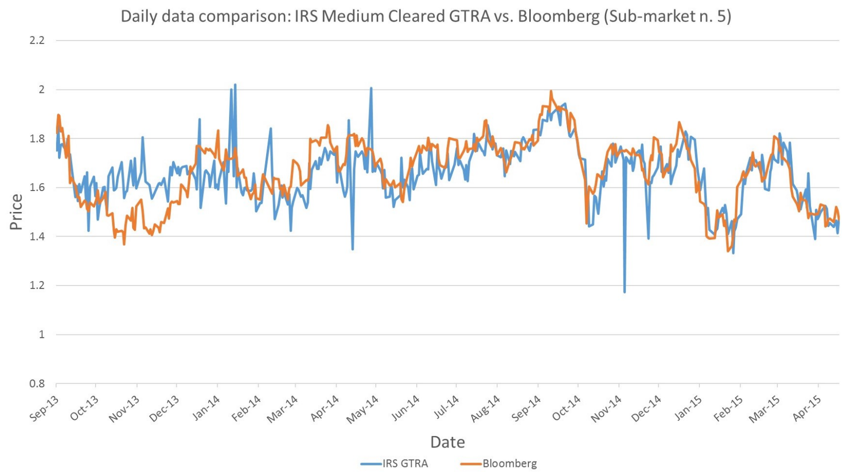
Official BIS descriptive statistics provide information for OTC derivatives by currency. At end-December 2014,[10] U.S. dollar interest rate swaps were 124 trillion in terms of outstanding notional amount, while in our dataset (*fix-to-floating* 3m3m plus 6m3m) the amount is about 14.6 trillion U.S. dollars, that is, close to the 12% of the whole USD IRS market. Although a direct comparison between BIS statistics and our sample would require a more detailed partition of the deals, not yet available in the BIS statistics, we observe a satisfactory coverage of IRS markets in our dataset.

In figure 15 (top), we compare IRS prices of the short maturity bucket in the cleared case (sub-market n. 4) from the GTRA database vs. data we obtain from *Bloomberg* corresponding to the USD 2Y curve. Time series trends are very similar during the entire reference period with only few exceptions, most of which are due to a sharper reported price from our data provider. Similarly, the comparison between the USD 5Y curve and the medium maturity bucket (sub-market n. 5) shown in the bottom panel of figure 15 confirms an overall coherence among both sources. There are some differences, especially in the first period, although on average both sources of data paints a similar picture. Those differences might be due to a grouping effect, since even if the medium bucket is mainly influenced by the 5Y tenor, the presence of other maturities in the bucket (e.g., 3Y, 4Y, 7Y) may affect the aggregated level.

[10] For references, see *http://www.bis.org/statistics/dt07.pdf*.

Figure 15: Comparison between GTRA and Bloomberg time series





IRS GTRA refers to the aggregated time series for deals belonging to sub-market 4 (top panel) and sub-market 5 (bottom panel). Bloomberg curves refer to USD 2Y and USD 5Y, respectively. Prices are in percentage.

Figure 16 focuses on the time series for the uncleared case with short maturity (submarket n. 7), and reveals quite erratic dynamics. Recall that the "uncleared" flag signals that the counterparty is more likely to be a corporation rather than another financial institution. Therefore, several different factors could be behind this apparently strange behaviour of the price series:

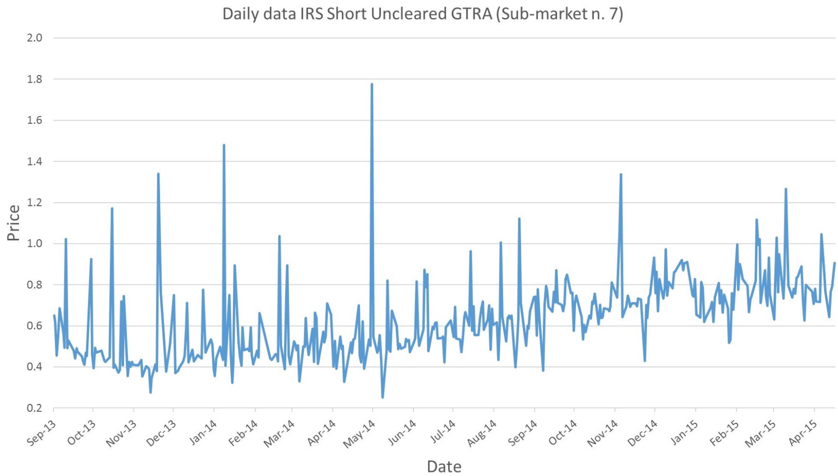
- an *up-front* is stated in the deal, that is, one of the counterparties receives a cash amount immediately. To balance it, the IRS fixed leg might be shifted to offset the upfront;
- the IRS pay-off could be highly customized, hence requiring a different fixed level;
- there is less liquidity in the IRS segment for the enterprises and banks may apply some relevant *mark-up* to offset the counterparty risk;
- a combination of the above factors.

3.3 Distress Indicator

Given a certain set of sub-markets representative of the global OTC market of swap instruments, we propose a way to measure their market conditions and to identify whether pairs of sub-markets are reciprocally co-dependent. We are particularly interested in sub-markets co–movements that point to distressed scenarios. To this end, we introduce an indicator of distress that synthesizes several dimensions of market condition. First, though, it is worth stressing that we do not rely on traditional concepts of default since markets cannot go bankrupt in a strict sense, although the absence of transactions can be interpreted in a similar way.

To assess the level of financial distress within each sub-market, we propose an indicator of distress that is able to capture several aspects related to financial stability. We assume that the main forces affecting the level of distress in a sub-market are represented by *(i)* the bid-ask spread of the prices, *(ii)* the volatility of the prices, *(iii)* the number of deals, and *(iv)* the volumes of notional traded amount. These forces reflect the perception that a wider bid-ask spread indicates deteriorated liquidity

Figure 16: GTRA Price Time Series for Sub-Market n. 7



Time series refers to deals belonging to sub-market 7. Daily prices are computed according to the weighted average of the prices of the contracts, where weights are based on the notional traded amount of the deals. Prices are in percentage.

conditions and that higher price volatility may suggest the presence of a distressed scenario. Similarly, a lower number of deals (or modest average notional traded amounts) may signal slowness in the process of adjusting prices, which may impact the capacity to close positions. These forces may interact, of course, but here we take a simple approach and focus only on the direct contributions of each.

In respect to point *(i)*, since we cannot directly deal with bid-ask quotes and do not know the parts involved in the transactions, we rely on the ratio between the maximum and the minimum of daily prices as a proxy for the bid-ask spread within a certain sub-market. This choice is motivated by the fact that a tight daily deviation between the maximum and the minimum is likely to imply that traded deals have been priced within a close interval. Although our choice is only a basic approximation of the bid-ask spread, work on estimation of the bid-ask spread highlights high/low prices as a way to measure bid and ask quotes in financial markets (Corwin and Schultz (2012); Deuskar et al. (2011)). For point *(ii)* we compute the dispersion in terms of the standard deviation of daily prices, while for points *(iii)* and *(iv)* we determine the daily number of deals (cardinality) and the daily average of the traded notional amounts, respectively. Finally, in order to get less noisy estimates we aggregate these measures on a weekly interval.[11]

To gauge the presence of distressed conditions, we note that even in the Basel model, although single default probabilities are present, the use of the 99.9% quantile for the capital charge is not related to a specific event, since it is merely a regulatory confidence level for estimation of the global credit portfolio's losses. Therefore, it seems reasonable to avoid selecting a given threshold above which we state that a certain sub-market experiences distress. Indeed, we suggest analysing sub-market reciprocal behavior in the tail corresponding to detrimental conditions. Future research may wish to explore setting a threshold level, however, so to design, for instance, a proper *backtesting* procedure for the model. Finally, note that the IRS price level represents an average of the *forward* (expected) interest rates over the IRS maturity. Hence, any turmoil in the IRS price and/or observed volumes could jointly reflect market, counterparty and liquidity aspects.

Tables 14, 15, 16 and 17 provide summary descriptions of the single components involved in the definition of the distress indicator. Specifically, for each sub-market we show the average (quarterly or monthly) of daily observations for, respectively, the logarithm of the ratio between the maximum and the minimum, the dispersion, the number of deals, and the average notional traded amount. These statistics show how sub-markets have evolved over time, possibly revealing some common pattern that might have affected the overall behaviour as well as the presence of specific features that characterize certain sub-markets.

Descriptive statistics provide some insight into sub-market behaviours during the sample period. Regarding the (ln) max/min deviations, for some sub-markets (1, 2, 3, 4) the first part of 2014 coincides with low mean values, whereas in the recent period they reach wider deviations. Conversely, other sub-markets (5, 6, 8, 9) show flattening or even de-

[11]If there are missing values due to lack of data, we replace them by the cubic spline interpolation of the available points. To limit potential biases due to outliers, for each sub-market we cut off 0.025 of the area in each tail of the reference sample distribution.

Table 14: Deviation between maximum and minimum

Sub-mkt	SEP 2013	Q4 2013	Q1 2014	Q2 2014	Q3 2014	Q4 2014	Q1 2015	APR 2015
1	0.35	0.14	0.10	0.15	0.37	0.37	0.49	0.37
2	0.29	0.24	0.19	0.58	0.71	0.65	0.54	0.55
3	0.05	0.04	0.04	0.19	0.23	0.23	0.20	0.27
4	0.55	0.42	0.54	0.48	0.75	0.86	0.81	0.64
5	1.06	1.06	1.08	1.00	0.83	0.81	0.70	0.76
6	0.43	0.41	0.33	0.34	0.30	0.31	0.42	0.36
7	0.54	0.51	0.80	0.57	0.72	0.66	0.79	0.30
8	1.10	0.98	1.09	0.99	0.83	0.79	0.68	0.62
9	0.53	0.44	0.39	0.33	0.36	0.34	0.33	0.40

The value in a certain cell stands for the natural logarithm of the ratio between the maximum and the minimum of deals' prices for the corresponding sub-market and period. Values are averaged among daily observations, separately for each sub-market. Column headings refer to the period (monthly or quarterly) considered in calculating mean values.

Table 15: Price dispersion

Sub-mkt	SEP 2013	Q4 2013	Q1 2014	Q2 2014	Q3 2014	Q4 2014	Q1 2015	APR 2015
1	0.34	0.11	0.07	0.04	0.11	0.10	0.15	0.12
2	0.29	0.26	0.24	0.30	0.32	0.29	0.21	0.21
3	0.20	0.10	0.09	0.25	0.28	0.25	0.17	0.20
4	0.06	0.04	0.04	0.05	0.09	0.09	0.11	0.08
5	0.43	0.40	0.46	0.43	0.36	0.32	0.25	0.24
6	0.33	0.37	0.34	0.32	0.28	0.25	0.19	0.19
7	0.15	0.16	0.20	0.13	0.17	0.17	0.22	0.10
8	0.53	0.49	0.51	0.48	0.41	0.36	0.31	0.28
9	0.44	0.41	0.37	0.34	0.31	0.27	0.24	0.34

The value in a certain cell stands for the standard deviation of the prices for the contracts belonging to the corresponding sub-market and period. Values are averaged among daily observations, separately for each sub-market. Column headings refer to the period (monthly or quarterly) considered in calculating mean values.

clining trends during the reference period. These patterns are generally confirmed when we consider the estimates for dispersions. In addition, it

Table 16: Number of traded deals

Sub-mkt	SEP 2013	Q4 2013	Q1 2014	Q2 2014	Q3 2014	Q4 2014	Q1 2015	APR 2015
1	2.3	1.7	1.5	4.2	5.7	7.5	5.1	4.4
2	3.1	3.0	2.7	24.2	51.0	46.2	35.9	31.6
3	1.8	1.9	2.6	25.3	46.1	47.2	46.9	37.6
4	24.7	28.6	39.1	33.2	40.8	57.2	50.3	48.4
5	183.2	252.0	292.2	257.2	295.0	332.3	309.8	244.1
6	195.5	241.5	228.1	223.5	272.7	311.1	320.5	251.7
7	6.4	5.3	6.3	5.2	7.2	9.6	8.5	4.5
8	25.4	21.0	25.6	24.4	33.2	40.7	22.5	16.5
9	30.2	25.0	21.6	18.4	35.8	44.1	21.3	13.6

The value in a certain cell stands for the number of deals corresponding to that sub-market and period. Values are averaged among daily observations, separately for each sub-market. Column headings refer to the period (monthly or quarterly) considered in calculating mean values.

Table 17: Notional traded amounts

Sub-mkt	SEP 2013	Q4 2013	Q1 2014	Q2 2014	Q3 2014	Q4 2014	Q1 2015	APR 2015
1	20.0	65.1	62.7	129.4	164.2	167.6	175.6	169.8
2	30.4	32.4	43.8	76.0	98.3	102.7	98.7	104.4
3	30.9	31.9	39.4	37.3	41.9	46.8	44.9	40.9
4	153.8	166.5	152.8	157.9	144.8	161.4	186.2	178.8
5	77.2	95.5	94.4	93.2	91.0	93.9	89.7	87.4
6	43.0	49.1	46.1	45.1	43.5	45.4	42.8	42.5
7	84.5	142.7	138.3	148.59	136.4	129.3	154.0	205.7
8	55.9	67.3	83.2	78.6	72.2	81.1	84.0	98.1
9	36.2	40.1	50.2	43.0	38.4	41.1	43.3	47.0

The value in a certain cell stands for the notional traded amount (in millions of U.S. dollars) corresponding to that sub-market and period. Values are averaged among daily observations, separately for each sub-market. Column headings refer to the period (monthly or quarterly) considered in calculating mean values.

may be of interest whether sub-markets with common contractual terms share similar trends. For instance, the absence of clearing agreements (sub-markets 7, 8, 9) does not seem to greatly affect the overall picture, since pairs of sub-markets (e.g., 5-8 and 6-9) with the same maturity and the same swap frequency legs but different clearing agreements have similar estimates. Furthermore, as expected for sub-markets with high volumes of transactions, those with cleared conditions (from 4 to 6) exhibit a smaller price dispersion than do the respective uncleared sub-markets (from 7 to 9). Finally, even for sub-markets with different swap leg frequencies but with the same maturity, the price dispersion is quite similar, for example, cluster 2 and the parallel cluster 5 in the second part of the sample period. Moreover, it may be the case that a sub-market has a high max-min deviation but low dispersion (e.g., sub-market 4). The last two measures describe an environment characterized by increasing trends in both the number of deals and the average notional traded amounts, although estimates for the last period seem to indicate a renewed decrease in transactions. In some cases (e.g., sub-markets 5-6), even though the average cardinalities are similar, the average notional traded amounts are quite different. These heterogeneous dynamics suggest considering a set of measures that will disentangle the overall level of distress for a certain sub-market. Therefore, the overall picture provided by these estimates suggests that a reasonable indicator of a sub-market's condition should rely on a comprehensive set of measures able to capture several market dimensions. For these reasons, we propose the following indicator of distress:

$$I_{i,t} = \ln\left(\frac{max_{i,t}}{min_{i,t}}\right) \times \frac{\sigma_{i,t}}{(Avgvolume_{i,t} \times Num_{i,t})} \tag{3.1}$$

where i and t are the indexes for the sub-markets and the weekly observations, respectively. *Max* and *min* denote the maximum and minimum of the weekly prices for each sub-market i at time t, respectively. Quantity $\ln\left(\frac{max_{i,t}}{min_{i,t}}\right)$ is lower bounded and increases when the deviation between the *max* and the *min*, becomes larger. The symbol σ stands for the standard deviation of the prices: its impact on the indicator of distress is positive, as greater volatility might be associated with distressed market conditions. Conversely, *Num* (i.e., the number of deals) has a negative effect since it is assumed that more traded deals implies that it is easier to find a counterparty, thus limiting liquidity risk. Lastly, the use of mean volumes (*Avgvolume*) indicates the average notional traded value of the deals and is introduced for liquidity purposes. We explicitly consider each driver (i.e., the deviation max/min, the dispersion, the cardinality, and the average traded amount) in the formula for the sake of clarity, although we are aware that there are some redundant issues related to the use of *Num* in the estimates for both dispersion and average volumes. Although market and liquidity risk drivers play an important role in the assessment of sub-market conditions, we provide a combined indicator of distress that aggregates a more comprehensive mix of effects. Relying on these components reflects the idea that the deviation between the max and the min is a rough measure of liquidity conditions since it simply represents a couple of extreme points while ignoring the stream of prices in the middle. Therefore, we correct this estimate by introducing price dispersion so as to mimic the effective distribution of the prices. Then, we further adjust this indicator by adding two other components to take into account the presence/lack of a sufficient number of deals (and/or average notional traded amount) and differentiate (*ceteris paribus* $\ln\left(\frac{max}{min}\right)$ and σ) between cases where the market is characterized by few deals (and/or with low average notional traded amount) and cases where we observe more deals and/or higher average notional traded amount.[12]

We believe that is reasonable to rely on this simple indicator that captures in a qualitative way (increasing or decreasing indications) the impacts of the different distress factors, thus allowing us to focus on the preliminary empirical results. Table 18 shows the average (monthly or quarterly) of the weekly observations of the indicator of distress as defined above.

Table 18 shows how sub-market distress has evolved over time. These estimates reflect the joint contributions of the single measures introduced above. To assess the level of distress within a sub-market, in principle one should observe the magnitude of this measure, since by construction higher values correspond to deteriorated market conditions. Table 18 reveals some stylized relevant facts. [13] The distress indicator, by

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[12]In addition, one could argue that Equation (1) can be improved by generalizing it with some parameters to be calibrated in some optimal way, such as:

$$I_{i,t}(\alpha,\beta,\gamma,\delta) = \ln\left(\frac{max_{i,t}}{min_{i,t}}\right)^{\alpha} \times \frac{\sigma_{i,}^{\beta}}{(Avgvolume_{i,t}^{\gamma} \times Num_{i,t}^{\delta})}. \tag{3.2}$$

[13]Estimates for September 2013 might even reflect the *backload* process of the deals. For instance, in the European Union, the EMIR regulation was in force February 2014. At that time also the deals already in existence were uploaded by a massive *backload* process. Hence

Table 18: Indicator of Distress

Sub-mkt	SEP 2013	Q4 2013	Q1 2014	Q2 2014	Q3 2014	Q4 2014	Q1 2015	APR 2015
1	12.21	1.63	0.44	0.24	0.16	0.11	0.17	0.10
2	9.61	1.97	1.88	0.28	0.05	0.05	0.12	0.04
3	0.09	0.32	0.05	0.28	0.04	0.03	0.02	0.04
4	0.01	0.01	0.01	0.01	0.03	0.01	0.01	0.01
5	0.04	0.03	0.03	0.02	0.01	0.01	0.01	0.01
6	0.02	0.02	0.01	0.01	0.01	0.01	0.01	0.01
7	0.29	0.51	0.42	0.22	0.31	0.22	0.30	0.05
8	0.46	0.62	0.32	0.34	0.18	0.13	0.16	0.15
9	0.24	0.23	0.15	0.25	0.11	0.06	0.12	0.28

The value in a certain cell stands for the indicator of distress (values multiplied by 10^9) corresponding to that sub-market and period. Values are averaged among weekly observations, separately for each sub-market. Column headings refer to the period (monthly or quarterly) considered in calculating mean values.

construction, does not have a practical or physical meaning although it allows some qualitative insights by looking at the *ranking* between the different markets. Hence it is worth noting that sub-markets 4 to 6 (which involve *bank-to-bank* most liquid sub-markets) show a very low distress level. If we analyze the other sub-markets (from 7 to 9), it seems that the uncleared ones (usually deals between *bank-to-enterprise*) are riskier. This is mainly due to the lack of liquidity and/or large min-max range.

In other words, this indicator allows us to capture in a formal and intuitive way the causal forces that could move sub-markets toward a distressed state. To switch from a useful but still descriptive representation to an investigation into how sub-markets are reciprocally influenced, we analyze how pairs of sub-markets are jointly dependent, that is, how sub-market distress co-moves. Therefore, we study the dependence structure of the co-movements by computing, for each sub-market, the following increments of the indicator of distress:

we doubt the quality of the oldest data. In fact, from the effective trade repository feed-running process, the distress indicators become lower and more stable. Note also that the *VIX* popular index, i.e., the volatility index of the S&P index level, did not reach abnormal levels at the end of 2014. In September 2013, the average level was 14.65%, just 50 bps higher than the average level of 2014 14.14%.

$$X_{i,t+1} = \frac{I_{i,t+1} - I_{i,t}}{I_{i,t}} \tag{3.3}$$

for $i = 1, ..., S$ and $t = 0, ..., T-1$. Hence, a sub-market that exhibits positive increments implies that it experiences deteriorated conditions, which became more serious if these variations become larger. Thus, our analysis is focused more on the right tail of the distributions of the increments, which corresponds to distressed market conditions.

3.4 Methodology

"Distress" is an extreme event, which can be viewed as an upper-tail event related to the process that describes the movement of the sub-market's status. We provide, for each pair of sub-markets, a *joint probability of distress*,[14] that is, the joint probability that both sub-markets simultaneously exhibit increments of the distress indicator above a certain threshold. This approach is similar to the one in Segoviano and Goodhart (2009), where the indicators known as Banking Stability Measures are presented. Our methodology is similar in that it views market players as a portfolio of players, and in providing a distress interdependence structure that is able to capture not only linear correlations but also nonlinear distress dependencies among the players in the system.

To compute the joint probabilities of distress, we split the analysis into three parts. First, once sub-markets have been set up, we study the form of correlation between each pair of sub-markets and how strong this relationship is. We exploit the family of Archimedean bivariate copulas (specifically the *Clayton*, *Gumbel*, and *Frank* copulas). The general theory of copulas[15] states that a joint distribution of some random variables can be decomposed into a function (called copula) that describes the interdependence structure among the considered variables and their

[14] The joint distress of pairs of sub-markets, as well as related terminology, are concepts introduced in this paragraph and in Section 3.3. Hereinafter, any reference to existing expressions must be considered in the context of our work.

[15] As a reference to the copula theory, we rely on the well-known results provided in Sklar (1959), Nelsen (2006), and Trivedi and Zimmer (2007).

marginal distributions. The reason for choosing copula functions from among the Archimedean family is that we want the possible dependencies to be comparable. In addition, the Archimedean family provides, through a unique parameter (i.e., θ), a proxy for the dependence degree between the two sub-markets. Second, after identifying the dependence structures for each pair of sub-markets, we produce a ranking based on the Kendall's tau correlation coefficients. Finally, we compute joint probabilities of distress at different marginal threshold levels.

We limit ourselves to bivariate copulas to study the dependence among pairs of sub-markets. This choice is due to the small number of available sub-markets. Generalization to multidimensional structures is possible and in the Appendix we briefly discuss the case with a copula dimension equal to 3.

In the following three subsections, we illustrate the technical details of the three steps of our study: identification of the copula function for each possible pair of sub-markets, the global ranking classification (based on Kendall's tau) among different pairs of sub-markets, and computation of the JPoD for pairs of sub-markets. A final ranking classification of the pairs of sub-markets based on the latter probabilities is also provided.

3.4.1 The preliminary copula-based procedure

Given S sub-markets and, for each sub-market, T time observations of the random variable of interest X (described above by Equation (3.3)), we can represent the data by means of a real-valued matrix X of dimension $S \times T$,

$$X = \begin{bmatrix} x_{11} & \cdots & x_{1t} & \cdots & x_{1T} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i1} & \cdots & x_{it} & \cdots & x_{iT} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{S1} & \cdots & x_{St} & \cdots & x_{ST} \end{bmatrix} = \begin{bmatrix} x_{1\cdot} \\ \vdots \\ x_{i\cdot} \\ \vdots \\ x_{S\cdot} \end{bmatrix}$$

where x_{it} represents the value of the observation t for the sub-market i and $x_{i\cdot}$ is the row-vector that contains all the values related to the sub-market i.

Our preliminary procedure takes as input this matrix and returns for each pair of sub-markets the most appropriate Archimedean copula and the corresponding parameter θ:

1. The procedure first derives the margin for each sub-market i by finding the empirical cumulative distribution function $\widehat{F}_i$ based on the corresponding T-dimensional row $x_{i\cdot}$. For each actor i, we are assuming the values $x_{i1}, \dots, x_{iT}$ as i.i.d. realizations drawn from the same univariate distribution.

2. For a fixed pair of different sub-markets, say (i, j), for each copula type (Cl =Clayton, Gu =Gumbel, Fr =Frank), the procedure computes the maximum value of the copula loglikelihood and the corresponding estimated value of the dependence parameter. Formally, it maximizes the function defined as

$$\theta \mapsto \ell_{(i,j),type}(\theta) = \\ = \sum_{t=1}^{T} \ln c_{type}\left(\widehat{F}_i(x_{it}), \widehat{F}_j(x_{jt}); \theta\right) + \sum_{t=1}^{T} \left(\ln f_i(x_{it}) + \ln f_j(x_{jt})\right),$$

(note that the second term does not depend on θ, nor on $type$) where $c_{type}(u_1, u_2; \theta)$ denotes the parametric expression of the density for the chosen copula ($type \in \{Cl, Gu, Fr\}$), and records the values $\ell^*_{(i,j),type}$ and $\theta^*_{(i,j),type}$ such that

$$\ell^*_{(i,j),type} = \ell_{(i,j),type}(\theta^*_{(i,j),type}) = \max_{\theta \in \Theta} \ell_{(i,j),type}(\theta).$$

Note that we are taking the pairs $\{(x_{it}, x_{jt}) : t = 1, \dots, T\}$ as T i.i.d. realizations drawn from the same bidimensional distribution.

3. For each possible pair (i, j) of different sub-markets, the procedure finds $\ell^*_{(i,j)}$, $\theta^*_{(i,j)}$, and $type^*_{(i,j)}$ such that

$$\ell^*_{(i,j)} = \max_{type \in \{Cl,Gu,Fr\}} \ell^*_{(i,j),type} \tag{3.4}$$

and $\theta^*_{(i,j)}$ and $type^*_{(i,j)}$ are the corresponding estimated parameter and the corresponding selected copula-type, respectively.

Equation (3.4) selects the copula that provides the best fit according to both AIC and SIC criteria[16]. Indeed, we have the best fit at the lowest value of the quantity

$$\begin{aligned}
AIC &= -2 \times (loglikelihood) + 2 \times (n.\,parameters)\\
&= -2 \times (loglikelihood) + 2\\
SIC &= -2 \times (loglikelihood) + \ln(n.\,observations) \times (n.\,parameters)\\
&= -2 \times (loglikelihood) + \ln(T),
\end{aligned}$$

respectively, and so at the highest value of the log-likelihood.

3.4.2 The correlation ranking

For each possible pair (i, j) of different sub-markets, the first step of the procedure selects the copula function, i.e., the type of copula ($type^*_{(i,j)}$) and the respective parameter ($\theta^*_{(i,j)}$). The goal of the second step is to produce a classification of the most dependent pairs of sub-markets. One way of measuring the strength of the dependence between two sub-markets relies on their parameter $\theta^*_{(i,j)}$; indeed, the Archimedean family of copulas provides a measure of dependence between (i, j). However, the theta parameter is related to the functional form of the copula and so values of the theta parameter for different copula functions are not comparable. We thus use the value of Kendall's tau[16] for each pair as the criterion for the ranking. Denoting by $\tau^*_{(i,j)}$ the value of the Kendall's tau coefficient as a function of $\theta^*_{(i,j)}$, our procedure considers each possible pair of different sub-markets and splits the final ranking of the pairs of sub-markets into two groups: the pairs with a positive Kendall's tau dependence coefficient (i.e., $\tau^*_{(i,j)} \geq 0$) and the ones with a negative dependence coefficient (i.e., $\tau^*_{(i,j)} < 0$). Finally, the procedure returns a decreasing ranking of the pairs of sub-markets based on $\tau^*_{(i,j)}$ for the first group, and, for the second group, an increasing ranking of the pairs based on the (negative) value of $\tau^*_{(i,j)}$. (Note that a negative dependence parameter is possible only for

[16]For further references, see Mahfoud (2012).

$type \in \{Cl, Fr\}$.)

Together with the two classes of rankings (positive and negative), the procedure returns for each pair (i, j):

- $type^*_{(i,j)}$ (based on the following code: $1 = Fr$, $2 = Gu$, $3 = Cl$),
- the value of the difference $diff\_theta_{(i,j)} = (\theta^*_{(i,j)} - \theta_{type^*_{(i,j)},ind})$ where $\theta_{type^*_{(i,j)},ind}$ is the value for the chosen copula $type^*_{(i,j)}$ corresponding to the independence case,[17]
- the estimated value for the Kendall's tau $\tau^*_{(i,j)}$ as a function of the theta parameter for the selected copula,
- the empirical value $e\_\tau^*_{(i,j)}$ of the Kendall's tau.

3.4.3 Joint Probability of Distress (JPoD)

Once the appropriateness of the selected copula model has been verified, the analysis continues by computing, for each pair of sub-markets, the joint probability that both simultaneously exhibit increments of the distress indicator above some threshold, that is, the joint probability of distress. We calculate this probability at different marginal threshold levels. Recall that in the Basel Vasiceck-Gordy model, the choice of a certain quantile (e.g., 99.9%) for the capital charge is not related to a specific event of distress, but it is merely a regulatory confidence level for estimation of the global credit portfolio's losses. Therefore, in our context, it seems reasonable to avoid selecting a given "distress threshold" and we thus analyse sub-markets' joint behaviour in the right tail at different marginal levels. More precisely, if we denote by X_i and X_j the increments of the distress indicator (defined in Section 3.3) for sub-markets i and j, respectively, then, for each pair (x, y) of real numbers, we have:

[17] The parameters that correspond to the independence case are: 0 (asymptotic value) for the Frank and the Clayton copulas, 1 for the Gumbel copula.

$$
\begin{aligned}
P(X_i > x, X_j > y) &= 1 - P(X_i \leq x \, or \, X_j \leq y) \\
&= 1 - F_i(x) - F_j(y) + P(X_i \leq x, X_j \leq y) \\
&= 1 - F_i(x) - F_j(y) + F(x, y) \\
&= 1 - F_i(x) - F_j(y) + C(F_i(x), F_j(y)),
\end{aligned}
$$

where F_i and F_j are the marginal cumulative distribution functions, F is the joint cumulative distribution function of the pair (i, j), and the last equality is due the Sklar's Theorem. Consequently, we define our joint probability of distress (JPoD) as:

$$
JPoD_{(i,j)} = 1 - u_i - u_j + C_{type^*_{(i,j)}}(u_i, u_j; \theta^*_{(i,j)})
$$

where $u_i, u_j \in [0, 1]$ are the levels for the marginal cumulative distribution functions F_i, F_j, typically chosen to equal 90%, 95%, and 99%.

3.5 Results

In this section, we present the results obtained applying the methodology introduced above to our dataset. In the next tables, sub-markets are defined as previously (see table 12). Copula types are: 1 (*Frank*), 2 (*Gumbel*), and 3 (*Clayton*). In addition, *"diff_theta"* refers to the theta parameter returned once a copula type is chosen minus the value of the theta parameter for the independence case for this type of copula. The *"e"* before the parameter refers to the empirical estimates (when no type of copula is imposed but estimates are computed on raw data). Our perimeter is composed by 25 pairs of sub-markets that exhibit positive estimated Kendall's tau correlations and 11 sub-markets with negative values. For the sake of clarity, we consider only the first half of the rankings, that is, the first 10 and 5 pairs for positive and negative Kendall's tau, respectively, thus focusing on those pairs of sub-markets with estimates the greatest distance from those of the independent case.

Positive Kendall's tau estimates reveal very interesting behavior if we focus on the pairs of sub-markets in the first positions of the ranking. Let us rewrite the nine sub-markets by an integer triple M_j, $j = 1...9$ as follows:

Table 19: Distress indicator: *Positive* Kendall's tau

Ranking	I Sub-mkt	II Sub-mkt	Copula	diff_theta	Kendall's tau	e_Kendall's tau
1	5	6	2	0.48	0.32	0.32
2	5	8	3	0.65	0.24	0.24
3	2	3	3	0.48	0.19	0.20
4	4	5	3	0.45	0.18	0.16
5	1	6	3	0.36	0.15	0.14
6	8	9	1	1.09	0.12	0.12
7	2	7	3	0.25	0.11	0.09
8	1	8	2	0.12	0.11	0.11
9	4	8	1	0.99	0.11	0.11
10	1	5	3	0.23	0.10	0.08

Ranking of reciprocal co-movements. Ranking is shown in a descending ordering based on positive Kendall's tau. The *I Sub-mkt* and *II Sub-mkt* columns show the pair of sub-markets selected by our procedure. The *Copula* column lists the chosen copula type. The *diff_theta* column sets out the theta parameter returned once a copula type is chosen minus the value of the theta parameter for the independence case. The empirical Kendall's tau is shown in the last column.

$$M_j = \left(f_j, t_j, c_j\right) \tag{3.5}$$

where

- f = frequency, 0 = 3m-3m, 1 = 6m-3m
- t = tenor range, 0 = short, 1 = medium, 2 = long
- c = clearing, 0 = cleared, 1 = un-cleared.

Hence, sub-markets span a very simple discrete space and we can define between each pair a *Manhattan*-like distance, such as:

$$d(M_i, M_j) \equiv \left|f_j - f_i\right| + \left|t_j - t_i\right| + \left|c_j - c_i\right|. \tag{3.6}$$

This simple framework reveals that the first four pairs (with respect to the Kendall's tau metrics) have the minimum distance between their components, i.e., $d(M_i, M_j) = 1$. This an appealing finding, since despite several issues related to the difficulty of identifying sub-markets, such as pioneering work with TRs data and the new distress indicator definition, these preliminary outcomes are highly intuitive. In addition, as shown by table 20, even negative estimates can occur. This is the case for pairs of sub-markets with quite different maturities and clearing conditions. Hence, sub-markets with different features are more prone to show opposite co-movements, while similarities in financial contractual terms are more likely to determine positive and high co-movements.

Table 20: Distress indicator: *Negative* Kendall's tau

Ranking	I Sub-mkt	II Sub-mkt	Copula	diff_theta	Kendall's tau	e_Kendall's tau
1	5	7	1	-2.23	-0.24	-0.23
2	3	8	3	-0.33	-0.20	-0.24
3	1	3	1	-1.52	-0.16	-0.17
4	7	8	3	-0.22	-0.12	-0.06
5	6	7	1	-0.98	-0.11	-0.10

Ranking of reciprocal co-movements. Ranking is shown in an ascending ordering based on negative Kendall's tau. The *I Sub-mkt* and *II Sub-mkt* columns show the pair of sub-markets selected by our procedure. The *Copula* column lists the chosen copula type. The *diff_theta* column sets out the theta parameter returned once a copula type is chosen minus the value of the theta parameter for the independence case. The empirical Kendall's tau is shown in the last column.

As shown in tables 19 and 20 for both positive and negative Kendall's tau rankings, there is a very high correlation among the empirical Kendall's tau ($e\_\tau^*_{(i,j)}$), which is calculated on the two vectors not processed through the copula procedure we employ, and the Kendall's tau ($\tau^*_{(i,j)}$), which we obtain according to the type of copula chosen for the pair of sub-markets (i, j) and its estimated parameter $\theta^*_{(i,j)}$. This correlation is equal to 0.991 for the positive ranking table and to 0.955 for the negative one, suggesting that the copula selection procedure provides a good fit.

Table 21: JPoD at different marginal threshold levels

JPoD ranking	Tau Ranking	I Sub-mkt	II Sub-mkt	Copula	JPoD 90%	JPoD 95%	JPoD 99%
1	1	5	6	2	4.4963%	2.1259%	0.4059%
2	8	1	8	2	2.2563%	0.9288%	0.1540%
3	2	5	8	3	1.5457%	0.3985%	0.0164%
4	6	8	9	1	1.4875%	0.3901%	0.0163%
5	9	4	8	1	1.4381%	0.3755%	0.0156%
6	3	2	3	3	1.4142%	0.3619%	0.0148%
7	4	4	5	3	1.3843%	0.3537%	0.0144%
8	5	1	6	3	1.3089%	0.3330%	0.0135%
9	7	2	7	3	1.2176%	0.3082%	0.0124%
10	10	1	5	3	1.2032%	0.3043%	0.0123%

Ranking based on JPoD estimates for different levels of thresholds. Ranking is shown in a descending ordering based on JPoDs. The *I Sub-mkt* and *II Sub-mkt* columns show the pairs of sub-markets selected by our procedure. Column *Copula* stands for the chosen type of copula. The *Tau Ranking* column shows the ranking based on the procedure exploited to select the type of copula for each pair of sub-markets. The last three columns set out the JPoD associated with different levels of the threshold (90%, 95%, and 99%).

In the last three columns of *Table 21* we report the JPoD at marginal levels for F_i and F_j, both equal to 90%, 95%, and 99%, respectively. Since we are studying the joint probability of distress, we focus on those pairs of sub-markets that exhibit positive Kendall's tau values (see table 19). The selection of these thresholds is intended to provide some insight into the relationships at the tail of the distribution, which corresponds to deteriorated market conditions. Preliminary results suggest that for the first two pairs the JPoD assumes quite relevant values, while for the other positions estimates are almost comparable. For instance, the first pair of sub-markets in the ranking position is $(i, j) = (5, 6)$, meaning that this pair of sub-markets has the most correlated increases in terms of percentage of the distress indicators (I_i, I_j) at the 90%, 95%, and 99% levels for the marginal cumulative distribution functions. This pair of sub-markets shares the same swap legs (6m3m), the same cleared conditions (cleared contracts in both sub-markets), but has different maturities (Medium vs. Long). In addition, they represent the two most active segments in the IRS market, as reported in table 13. Therefore, it seems that the two most important sub-markets in terms of number of deals and traded notional amounts are also highly co-dependent. At a first glance, we observe slightly different rankings compared to those shown in table 19. However, JPoD and Kendall's tau rankings are coherent once we focus on a certain type of copula, that is, given the same copula, the ordering for pairs of sub-markets is the same for both rankings. Finally, we briefly analyse the second position in table 21, that is $(1, 8)$. This pair of sub-markets has different swap legs (3m3m vs. 6m3m), different cleared conditions (cleared vs. uncleared), and different maturities (Short vs. Medium). Still, they share a high probability of joint distress, thus supporting the need for further investigation into the features that impact reciprocal influence between sub-markets that are apparently very distant. Hence, similarities between financial and contractual terms seem to be responsible for stronger co-dependences in many cases, although the emergence of high values for JPoD in regard to quite different sub-markets (pair 1,8) suggests the presence of reasons other than contractual terms. This underlines the need to identify the key players operating in these OTC IRS markets, since their roles may influence co-movements between apparently different sub-markets.

3.6 Conclusions and future research

The financial crisis of the last decade motivated a growing literature on how to model and predict financial distress. Some concepts, such as *systemic risk*, the *contagion* effect, and *cascade* defaults have received a great deal of attention. Nevertheless, a "new normal" for the risk management field has not yet been established. If we consider the financial system as a whole, several challenges need to be overcome, such as the huge number of risk factors and financial products, their dependence structures, the lack of complete and granular data about the financial system, the quality of available data, and the measures to be used to capture and predict market co-movements. To partially address these issues, we exploite and combine in an innovative way some new ingredients, namely, the OTC derivatives data provided by trade repositories along with the JPoD approach recently suggested by the International Monetary Fund. To the best of our knowledge, this is the first attempt that exploits micro-founded data from trade repositories to study co-dependence between financial sub-markets. Specifically, we focuse on the interest rate derivatives as a significant fraction of the OTC market and we defined a distress indicator by combining four different distress drivers: liquidity, average traded volumes, volatility, and bid-ask proxies. We then use this framework to study the *distress dependencies* of some OTC sub-markets that we built based on contractual and financial features. By analysing both the descriptive results and the joint probabilities of distress, the proposed technique seems promising for assessing market co-movements from a financial stability perspective, with intuitive preliminary results. Similarities between financial and contractual terms seem to be responsible for stronger co-dependences, although high values for JPoD even regarding quite dissimilar sub-markets suggest the presence of other drivers that need to be investigated in future research (such as the role of key market players active across different sub-markets, something not possible to identify with our dataset). There is also a need for a more finely tuned distress definition to calibrate a more general distress indicator formula that can be applied for *backtesting* procedures, that is, to assess its prediction properties. Furthermore, other asset classes (equity, credit, forex, etc.) could be exploited to implement a financial "classical" top-down sub-market segmentation. Finally, more knowledge about the quality of the TRs' internal data would be very helpful.

Appendix A.

Copula definition

Copula functions provides a mathematical instrument for the modelling of the multivariate stochastic dependence structure. In particular, copulas take into account various kinds of stochastic dependence structures among actors, without any assumption on the one-dimensional marginal distributions. The concept of copula was introduced during the forties and the fifties with Sklar (1959), but the evidence of a growing interest in this kind of functions in statistics started only in the nineties (see Hoeffding (1994) and Nelsen (2006)). Copulas are functions that join or "couple" multivariate distribution functions to their one-dimensional marginal distributions. The advantage of the copula functions and the reason why they are used in the dependence modelling is related to the Sklar's theorem (see Sklar (1959)). It essentially states that every multivariate cumulative distribution function can be rewritten in terms of the margins, i.e. the marginal cumulative distribution functions, and a copula. More precisely, we have the following definition and results.

Definition 1 *A d-dimensional copula* $C(\mathbf{u}) = C(u_1, ..., u_d)$ *is a function defined on* $[0,1]^d$ *with values in* $[0,1]$*, which satisfies the following three properties:*

1. $C(1, ...1, u_i, 1, ..., 1) = u_i$ *for every* $i \in \{1, ..., d\}$ *and* $u_i \in [0,1]$*;*
2. *if* $u_i = 0$ *for at least one i, then* $C(u_1, \ldots, u_d) = 0$*;*
3. *for every* $(a_1, ..., a_d), (b_1, ...b_d) \in [0,1]^d$ *with* $a_i \leq b_i$ *for all i,*

$$\sum_{j_1=1}^{2} \cdots \sum_{j_d=1}^{2} (-1)^{j_1+\ldots+j_d} C(u_{1,j_1}, ..., u_{d,j_d}) \geq 0$$

   where, for each i, $u_{i,1} = a_i$ *and* $u_{i,2} = b_i$*.*

Proposition 1 *Let F be a multivariate cumulative distribution function with margins* $F_1, ..., F_d$*. Then there exists a copula* $C : [0,1]^d \to [0,1]$ *such that, for every* $x_1, ..., x_d \in \overline{\mathbb{R}} = [-\infty, +\infty]$*, we have*

$$F(x_1, ..., x_d) = C(F_1(x_1), ..., F_d(x_d)).$$

If the margins $F_1, \ldots, F_d$ *are all continuous, then C is unique; otherwise C is uniquely determined on* $F_1(\overline{\mathbb{R}}) \times \cdots \times F_d(\overline{\mathbb{R}})$*.*

Conversely, if C is a copula and $F_1, \ldots, F_d$ are cumulative distribution functions, then F defined by (1) is a multivariate cumulative distribution function with margins $F_1, \ldots, F_d$.

In the case when f and $f_1, \ldots, f_d$ are the marginal probability density functions associated to F and $F_1, \ldots, F_d$, respectively, the copula density c satisfies

$$f(x_1, \ldots, x_d) = c\Big(F_1(x_1), \ldots, F_d(x_d)\Big) \prod_{i=1}^{d} f_i(x_i).$$

There are different families of copula functions that capture different aspects of the dependence structure: positive and negative dependence, symmetry, heaviness of tail dependence and so on. In our work, we limit ourselves to the principal copula functions of the Archimedean family (namely, Gumbel, Clayton and Frank copulas), which model, through a unique parameter θ, situations with different degrees of dependence.

For more details on copula theory, we refer to the various excellent monographs existing in literature, such as Joe (1997), Nelsen (2006) and Trivedi and Zimmer (2007).

Archimedean family of copulas

Here we just recall, in the bivariate case, the principal copula functions belonging to the Archimedean family that we employ in our analysis Huynh et al. (2014).

- **Frank copula**:

$$C_{Fr}(u_1, u_2; \theta) = -\frac{1}{\theta} \ln\left(1 + \frac{(e^{-\theta u_1} - 1)(e^{-\theta u_2} - 1)}{\exp(-\theta) - 1}\right).$$

  The parameter $\theta \in \Theta = (-\infty, +\infty) \setminus \{0\}$ tunes the degree of the dependence. The limiting cases $\theta \to \theta_{Fr,ind} = 0$ correspond to independence.

- **Gumbel copula**:

$$C_{Gu}(u_1, u_2; \theta) = \exp\left\{-\left[(-\ln u_1)^{\theta} + (-\ln u_2)^{\theta}\right]^{\frac{1}{\theta}}\right\}.$$

The parameter $\theta \in \Theta = [1, +\infty)$ tunes the degree of the dependence. In particular, the value $\theta = \theta_{Gu,ind} = 1$ corresponds to independence (indeed, we get $C^{Gu}(\mathbf{u}; 1) = \prod_{i=1}^{d} u_i$).

- **Clayton copula**:

$$C_{Cl}(u_1, u_2; \theta) = \left(u_1^{-\theta} + u_2^{-\theta} - 1\right)^{-\frac{1}{\theta}}, \qquad \theta \in \Theta = [-1, +\infty) \setminus \{0\}.$$

The parameter θ controls the degree of the dependence. The limiting case $\theta \to \theta_{Cl,ind} = 0$ corresponds to independence.

Kendall's tau

Consider two random variables X, Y with continuous marginals F_1, F_2 and joint cumulative distribution function F [18]. The Kendall's tau correlation coefficient is defined as:

$$\tau(X, Y) = P\{(X_1 - X_2)(Y_1 - Y_2) > 0\} - P\{(X_1 - X_2)(Y_1 - Y_2) < 0\}$$

where (X_1, Y_1) and (X_2, Y_2) are two independent pairs of random variables from the joint distribution F. It can be written in terms of the copula function as follows:

$$\tau(X, Y) = 4 \int_0^1 \int_0^1 C(u_1, u_2)\, dC(u_1, u_2) - 1.$$

In particular, for the Archimedean copulas, the Kendall's tau can be expressed as a function of the dependence parameter θ:

$$\tau(X, Y) = \begin{cases} 1 + 4\theta^{-1}[\theta^{-1} \int_0^\theta t/(e^t - 1)\, dt - 1] & \text{Frank} \\ 1 - \theta^{-1} & \text{Gumbel} \\ \theta/(\theta + 2) & \text{Clayton.} \end{cases}$$

[18] For further details, see Trivedi and Zimmer (2007).

Appendix B.

Robustness check

In the chapter we focus on a copula dimension equal to 2. Generalizations to higher dimensions are feasible, although it is worth remembering that in our case we are dealing with only nine sub-markets. Below, we briefly report the trivariate case and present estimates similar to those in Table 19. The algorithm retains the possibility of choosing between three different copulas (Frank, Gumbel, and Clayton). We estimated all possible triple results, namely, 84 positions (the number of possible combinations for nine sub-markets), although for the sake of conciseness we report only the first 10 positions. Both tables show the value of the parameter estimated by our procedure minus the parameter for the independence case (*diff_theta*). Table 3.6 is ordered by decreasing maximum likelihood; Table 3.6 is obtained by ordering the triples by decreasing *diff_theta*.

Terns that appear in the first 10 positions of both tables should be used in the financial analysis of the sub-markets, since those should represent the most trustworthy results as they are found in two different ordering criteria. Triples (4,5,8), (5,6,8), and (1,5,6) appear in both Table 3.6 and Table 3.6. The first two pairs share similar contractual terms, that is, they refer to swap frequency legs equal to (6m3m) and present a short Manhattan–like distance (it is 4 in both cases, computing by summing distances among each couple in the tern). Conversely, tern (1,5,6) shows quite different features and presents a higher distance (it is 6). Thus, even in the trivariate case, dissimilarity among contractual and financial terms can imply strong co-movement. Below, we analyse the tables in more detail, providing a comparison with the sub-markets that appeared to be co-dependent in the bivariate case as shown in Table 19.

The ranking in Table 3.6 is based on *diff_theta*. Estimates are coherent with those in Table 19: in the first positions we observe combinations of pairs (5,6), (5,8), (2,3), and (8,9), that is, pairs of sub-markets that are strongly co-dependent in the bivariate case are more likely to influence co-movement also in the trivariate case. Hence, relevant relationships among pairs of sub-markets seem to emerge regardless of the dimension of the copula. In addition, we also compare these results to those provided in Table 21, which gives the output of JPoD (not implemented in the trivariate case): we find again that sub–markets (5,6), (5,8), (2,3), and

(8,9) hold top positions in the ranking. Finally, in Table 3.6 we show how sub-markets are ranked based on the maximization of the log-likelihood. Even in this case (similar to the one discussed in Section 5), results are coherent among Tables 3.6 and 3.6 once we consider the estimates within the chosen type of copula. Overall, this is further evidence of the robustness of our procedure; however, increasing the copula dimension too much may lead to meaningless results when having few sub-markets.

Table 22: Ranking based on diff_theta (Top 10 Positions)

Ranking ML	I Sub-mkt	II Sub-mkt	III Sub-mkt	Loglikelihood	Copula	diff_theta
18	2	5	6	3.81	1	1.11
19	3	5	6	3.60	1	1.07
21	2	3	6	3.21	1	1.02
24	4	8	9	2.79	1	0.91
36	1	8	9	1.65	1	0.70
1	4	5	8	10.54	3	0.48
2	5	6	8	9.69	3	0.44
57	3	5	9	0.60	1	0.42
61	2	4	7	0.47	1	0.37
3	1	5	6	7.70	3	0.37

Ranking of co-movements when copula dimension is equal to 3. Ranking is shown in a descending ordering based on positive *diff_theta*. The *I Sub-mkt*, *II Sub-mkt*, and *III Sub-mkt* columns show the triple of sub–markets selected by our procedure. The *Copula* column lists the chosen copula type. The *diff_theta* column shows the theta parameter returned once a copula type is chosen minus the value of the theta parameter for the independence case. Column *Ranking ML* refers to the ranking based on maximization of log-likelihood. Finally, we report for each combination the respective max log-likelihood.

Table 23: Ranking based on max log-likelihood (Top 10 Positions)

Ranking	I Sub-mkt	II Sub-mkt	III Sub-mkt	Loglikelihood	Copula	diff_theta
1	4	5	8	10.54	3	0.48
2	5	6	8	9.69	3	0.44
3	1	5	6	7.70	3	0.37
4	1	5	7	7.70	1	0.37
5	4	5	6	7.23	3	0.36
6	4	5	7	7.23	1	0.36
7	5	8	9	7.21	3	0.37
8	6	7	8	7.21	1	0.37
9	6	7	9	7.21	1	0.37
10	1	5	8	6.08	3	0.33

Ranking of co-movements when copula dimension is equal to 3. Ranking is shown in a descending ordering based on the maximized log-likelihood. The *I Sub-mkt*, *II Sub-mkt*, and *III Sub-mkt* columns show the triple of sub-markets selected by our procedure. The *Copula* column lists the chosen copula type. The *diff_theta* column sets out the theta parameter returned once a copula type is chosen minus the value of the theta parameter for the independence case.

Chapter 4

Regulation of Multilateral Development Banks (MDBs): is it needed?

4.1 Introduction

This chapter focuses on the key findings on the global financial architecture agreed at international level in the aftermath of the financial crisis of 2008 and on the process which led to a stronger surveillance and collaboration at an international scale. In the meantime, a relevant part in the credit support to the real economy in less-developed countries has been increasingly provided by the supranational development banks. We selected a subsample of ten Multilateral Lending Institutions (MLIs) that together account for almost a trillion US dollars of the worldwide supranational lending[1]. Our sample includes: African Development Bank (AfDB), Asian Development Bank (ADB), Central American Bank for Economic Integration (CABEI), Nordic Investment Bank (NIB) International Bank for Reconstruction and Development (IBRD) and International Finance Corporation (IFC), European Investment Bank (EIB), European Bank for Reconstruction and Development (EBRD), Inter-American Development Bank (IADB) and Inter-American Investment Corporation

[1] Data as at end-2015.

(IIC)[2]. We analyse their balance sheet to show a growing lending to non-financial private sector in the meantime when domestic banks of most advanced economies[3], especially in the Euro area, show an opposite behaviour. We argue that this difference in providing support to the real economy is due to different characteristics of MDBs that allow them to act counter-cyclically in the event of a crisis and to different regulatory capital requirements the traditional banking sector is subject to. While regulation has progressively become stricter for commercial banks, MLIs lack a common supervisory framework being the only respondent to sovereign mandates and bylaws. The chapter proceeds as follows. After a broad overview of the main concepts regarding MLIs in section 4.2, section 4.3 retraces the historical background of the need for a sounder financial regulation and some drawbacks of the latter. Section 4.4 assesses the role of MLIs into the economy. Section 4.5 exposes the lack of a proper unified regulatory hat for MLIs and section 4.6 concludes with an open question.

4.2 What are Multilateral Lending Institutions (MLIs)

Multilateral Lending Institutions (MLIs) or Multilateral Development Banks (MDBs) are supranational institutions, owned or established by governments of two or more countries, to pursue specified policy objectives such as the promotion of social and economic development in less-developed member countries, help in regional integration and expansion of cross-border trade. Renewed goals are set up in the Development Committee Discussion Note prepared in April 2015 jointly by African Development Bank, Asian Development Bank, European Bank for Reconstruction and Development, European Investment Bank), Inter-American Development Bank, International Monetary Fund and World Bank Group[4]. They include:

- support of international action on global/regional development issues;

[2]See the Appendix A for a description of MDBs main activities.

[3]Advanced economies comprise Australia, Canada, Denmark, the Euro area, Japan, New Zealand, Norway, Sweden, Switzerland, the United Kingdom and the United States.

[4]The full note is available at the webpage: `http://siteresources.worldbank.org/DEVCOMMINT/Documentation/23659446/DC2015-0002(E)FinancingforDevelopment.pdf`.

- promotion of local capital markets and access facilitation to local currency finance;
- strengthening of domestic resource mobilization and public expenditures;
- improvement of quality and efficiency of their services to increase the development impact;
- engagement and incentive to private finance;
- enhancement of the impact of private sector via inclusion and sustainability; and
- improvement in coordination and alignment among MDBs.

Historically MDBs worked under the clause of conditionality. Conditionality refers to a commitment of MDBs borrowers to take the necessary actions regarding policies, provision of technical inputs, implementation, and safeguard measures to produce the intended development results. This principle typically applies to the actions that a borrower must take to obtain the loan so that failure to comply with these conditions may result in suspension, cancellation, or recall of the loan. However, according to Bhargava (2006) recently the attitude of MDBs changed towards this principle by reducing the average number of conditions per lending operation while looking for more evidence of borrowers' commitment to reforms and are rewarding reforms already undertaken, increasing transparency and encouraging public debate on the need for reform.

Humphrey and Michaelowa (2013) acknowledge the far-reaching implications of MDBs activities about international development and provide the determinants of lending from a demand-side perspective. They confirm a theoretical argument by which a demand for a loan depends, among other things, on the balancing of the governance structures of the MDBs between their borrowing and non-borrowing shareholders and on the implications of this governance structure for loan cost and bureaucratic procedures. The supply-side research on MDBs instead typically assumes that all countries eligible to borrow from an MDB will always want to do so, the rationale behind being represented by favourable interest rates compared to other ways of financing and the fact that it is possible to appoint MDBs without tender due to their special legislative and not-for-profit status. The important question to be asked in this case is what factors might lead an MDB to award a loan to a country or not. If the country is a shareholder, the MDB's mandate encourages and impose the MDB to grant financial support to viable projects that will improve citizens lives. This applies in particular to sensible issues such as hunger in the world, health, integration, infrastructures, schooling, clean energy, research and development. A shareholder country engages with an MDB able to promote the same desirable values and *Sustainable Development Goals (SDG)* as it would, in exchange from the MDB's side the commitment to achieve its objectives and at the same time not to make profits or retain returns without a reasonable justification. Projects in non-shareholder countries can also be promoted in solidarity to help to eradicate problems at their roots. In this framework, an important tool is represented by the *Mandates*. A mandate is defined as a partnership entered by the MDB with third parties to achieve mutual objectives and which is passed on financial support pledged by a third party. The partnership takes the form of a legal agreement between the MDB and a third party (e.g., a supranational body, an institutional donor, etc.) with the key criteria of pursuing common objectives and accepting the third-party support or funding in the form of guarantees, blending or direct investment, and it has the advantage to boost the impact rather than the volume of lending by supranationals while keeping at the same time the financial solidity of the MDB.

While deciding for approval or follow-up of the projects MDBs rely on a broad spectrum of competencies, internal research, and monitoring tools that consider other non-financial factors (e.g., the added value and the social impact of a project on a community) compared to the lending approval of commercial banks. MDBs share the know-how of their staff also by providing advisory and technical assistance. A business preference for economically viable projects aims at keeping MDBs balance sheets financially robust and at the same time avoid pursuing risk-seeking behaviours. The paid-in capital from sovereigns, the disposable of callable capital in some cases and MDBs business strategy contribute to its overall good credit rating that is issued by the Rating Agencies. We reckon the high rating as a general feature of supranational institutions as shown by figure 17. One reason for that is a beneficial treatment for MDBs in case of a sovereign borrower's default called *Preferred Creditor Status (PCS)* or *Preferred Creditor Treatment (PCT)* consisting in priority over other creditors in debt repayment. It has no legal basis, rather constituting a market practice attributable to the incentives faced by distressed sovereign borrowers. Thanks to this clause MLIs benefit the first claim over any funds available from the debtor whereby distressed sovereigns service their obligations to some lenders even while defaulting on other debts. this leads to an effective increase in seniority of MDB claims compared to claims that would otherwise have the same seniority as stated by Perraudin et al. (2016). This paper assessed that, although there is no legal basis for PCS, it improves the credit quality of the institutions as perceived by the bond market, since implied spreads with no allowance for PCS are higher than those observed when PCS is introduced. Another advantage of PCS is that member states can grant MLIs loans preferential access to foreign currencies in the event of a country foreign exchange crisis. This status has two consequences: it increases the portfolio quality which helps to get cheaper funding on the market and it ensures that the resources of the supranational institution are safe in distress time when other creditors face substantial uncertainty about full repayment. It is needed so to ensure that the institution can act as a credible lender of last resort, formulate policies necessary for restoring economic stability and restructure a manageable level of debt. High credit ratings also have another motivation that is funding. Most MDBs have as the main source of funding the bonds issuance on international capital markets. Therefore, it is important for them to keep a high credit profile so to guarantee the capital inflows and a low cost of funding. There is a variety of bonds available to investors including medium–term notes, local currency bonds, benchmark bonds, targeted bonds, green bonds and commercial papers. Most products are issued in several currencies, and some are eligible as collateral for the open market operations.

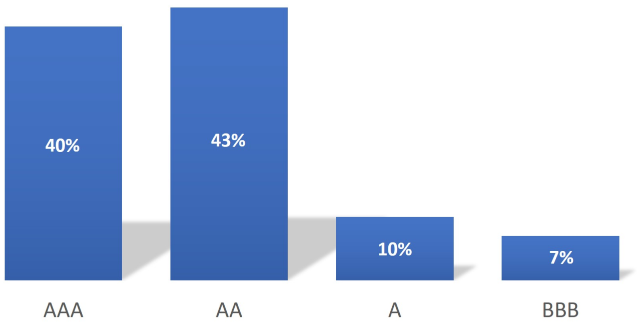
Credit Rating Agencies such as Standard & Poor's do recognise supranational specificities while making their annual assessment, e.g., S&P Global Ratings (2016). Here S&P describes an ad-hoc methodology to assess the stand-alone credit profile of the supranational based on the business profile and financial profile of the institution. After the stand-alone assessment of the institution S&P adjusts its final rating by estimating the notches of uplift stemming from the callable capital if any. S&P considers only the callable capital from shareholder countries rated above the institution itself because of possible difficulties in cashing capital during a distress scenario by countries with a lower credit worthiness.

According to Perraudin et al. (2016), the ability of MDBs to realize their international development objectives is limited in practice by the need to maintain access to low–cost financing in international debt markets, since the scale of their activities and the level of risk that they can assume are limited by the market's view of their solvency as reflected in credit spreads and agency credit ratings. Although these motivations make MLIs eager to remain well capitalized, they are quite constrained on the achievement of this goal through an intervention on equity, via a capital increase, or through the sustainable generation of annual net surplus, the reasons being difficult negotiations with shareholders and mandate to keep low returns. Therefore, to achieve high credit status MDBs act on the credit quality determinant given by the degree to which MDB portfolios are diversified or concentrated. Like conventional commercial banks, the level of diversification across geographical regions and sectors is an significant influence on the main credit quality measures such as the probability of default. Unlike most commercial banks, some MDBs have, also, significant single name concentration risk in that they have relatively high proportionate exposures to particular sovereigns. Consequently, they pursue business strategies that benefit from the diversification of main lending operations. A risk management option is represented by an *Exposure Exchange Agreement (EEA)* consisting of an innovative solution to exchange a particular exposure or pool of exposures between MDBs in order to reduce MDBs concentration risk. As reported by Belhaj et al. (2017), the first EEA was approved by the African Development Bank (AFDB), the Inter-American Development Bank (IADB) and International Bank for Reconstruction and Development (IBRD) in November 2015 and the first three MDB EEA transactions were signed between these institutions on 15th December 2015.

4.3 Financial crisis, banking sector crisis and increased regulation

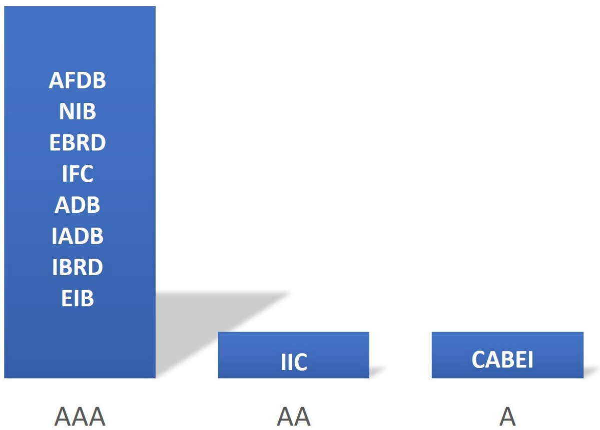
As assessed by Moshirian (2011) the 2007-2008 global financial crisis has provided a unique opportunity to go beyond economic data and attempt to capture cross–border financial data and other information that could assist international and national institutions to measure and manage financial risk more effectively to avoid regulatory arbitrage. Generally, to policy-makers and academic researchers financial crisis provide a window of opportunity to reflect upon the role of financial and banking regulation and on the cooperation between public and private sectors to

Figure 17: Overall rating distribution of supranationals in 2016



Source: authors elaboration of data from S&P Global Ratings (2016).

Figure 18: Rating distribution of selected MLIs in 2016



Source: authors elaboration of data from S&P Global Ratings (2016).

restore investors' confidence in the economy[5]. Brownbridge and Kirkpatrick (1999) takes the case of the Asian crisis of 1999[6] to analyse the

[5]On the latter topic see e.g. Checki and Stern (2000).

[6]For a review of the Asian crisis, see e.g. Goldstein (1998), Wade (1998) or Corsetti et al. (1999).

financial sector regulation as a contributory factor. Financial regulation becomes particularly relevant for developing economies where financial infrastructures may boost the development process and facilitate an efficient use of resources for economic growth. At the same time, a lack of supervision and regulation of financial markets configures as a contributory factor to financial failures in distress time. Nobel laureate Joseph Stiglitz as chief economist of the World Bank about the same Asian crisis wrote[7] that "financial and capital market liberalization - done hurriedly, without first putting into place an effective regulatory framework - was at the core of the problem". Goodhart (2008) points out some regulatory failures behind the 2008 financial turmoil based on UK experience: form of deposit insurance, bank solvency regimes, central banks' money market operations, commercial bank liquidity risk management, lack of counter-cyclical instruments, the burden of cross–border defaults. Even IMF[8] identified several areas in which reforms were needed for a safer financial architecture, such as surveillance of systematic risk, international coordination of macro-prudential responses, cross–border arrangements for financial regulation and funding for liquidity support. In 2009 the Financial Stability Forum (FSF) became the Financial Stability Board (FSB) to collaborate with other international institutions for safeguarding the global financial stability and in the same years G20 emerged as a major global forum to deal with major economic and financial decision-making process[9] .

Many of the issues above have been amended by the legislator[10], translating at the same time into a heavier reporting burden for compliance especially on financial institutions. In the aftermath of the financial crisis of 2008 blighted market conditions and stricter national and international regulatory measures reduced international capital flows and banking activity. This translated into a challenging fundraising when Basel rules on capital requirements were becoming more demanding, not only for commercial banks but also for insurance companies and consumer credit

[7] In Stiglitz (2000).

[8] In Blanchard (2009).

[9] We remind the reader on international cooperation, convergence and harmonization on regulation to see e.g. the articles Howarth and Quaglia (2016), Helleiner and Pagliari (2011) and the book Chey (2014).

[10] Fratzscher et al. (2016) found evidence that higher capital buffers improved aggregate bank stability after the great financial crisis, especially in countries with relatively poor institutions, suggesting that bank supervision/regulation and institutions tend to be substitutes rather than complements.

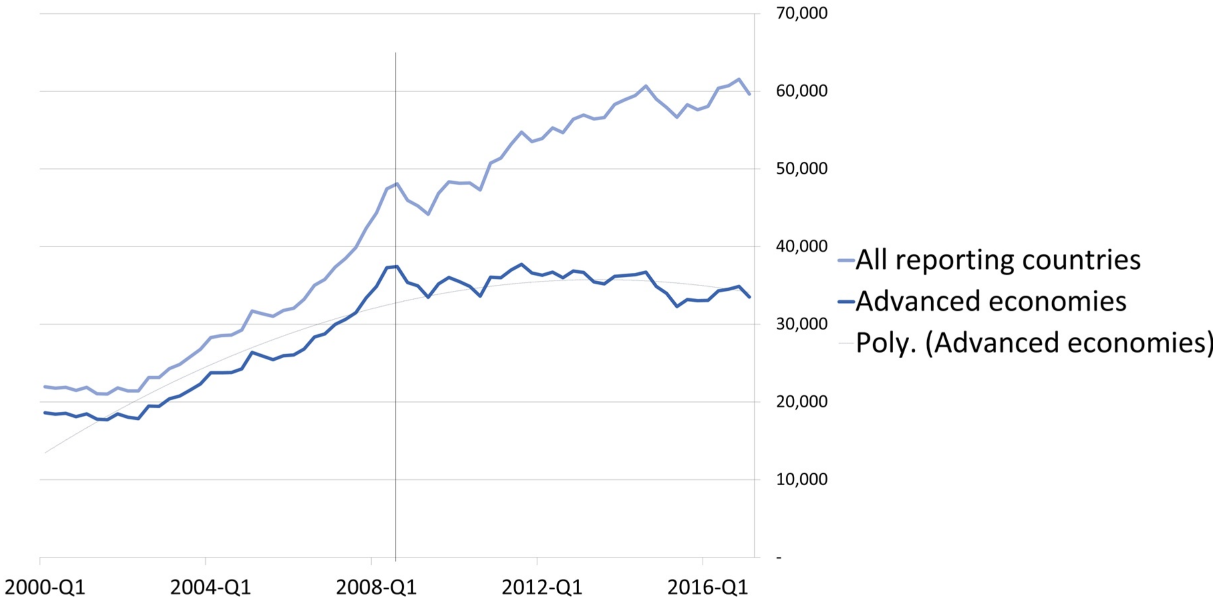
companies. Ultimately this caused less credit to the economy, raising potential long–run consequences in credit supply. Rajan and Ramcharan (2016) found that financial regulation after the great depression may have helped to render the effects of the initial collapse persistent. Ferri (2017) the new Basel rules impacted negatively on cooperative and savings banks, especially in the Eurozone. Reduced international capital flows and bank activity were instead as much the result of national and regional regulatory measures as they were a function of market conditions according to Epstein and Macartney (2016). Stricter capital requirements stemming from the increased regulation reversed into harsh times for banks' lending: where funding was not enough to reach a sufficient capitalization, the result was a contraction in banks assets and a decrease of banks' lending activities.

We analyse data from BIS total credit statistics to assess the lending trend from domestic commercial banks. More specifically, data are BIS long series on total credit, at quarterly frequency, from the Lending sector *Banks, domestic* to the Borrowing sector *Private non-financial sector*. The data analyzed answer the research question on who is providing support to the real economy: we decided not to analyze the intra–banks financial lending, but the credit just to the private sector. Furthermore, we choose consolidated domestic banking statistics not to bias the geographic coverage comparison. We show two graphs (Figures 19 and 21) regarding the stocks of the banks' lending before of seeing in the graphs (Figures 20 and 22) the ratio between total credit and Gross Domestic Product (GDP). The latter regards the effect of a shrinkage of credit to the real economy and is an important indicator for detecting the build-up of cumulative vulnerabilities during credit booms, when the ratio of credit to GDP deviates from its trend by a specified amount. Borio and Lowe (2002) refer to this deviation as the "credit gap". They define similarly other measures such as "asset price gap" and "investment gap", and calculate the various gaps using only information that would have been available to the policymakers at the time that he/she was assessing whether or not a boom existed (*ex–ante information*). They assess the validity of combinations of indicators over multiple horizons to account for the difficulty in predicting the timing of a crisis. They find that keeping a cumulative trace of imbalances has a better predictive power, and among the indicators examined the credit gap results the best correctly predicting the largest number of crises with the lowest noise to signal ratio.

Our results show a decreasing trend of total credit from domestic banks to non-financial private sectors for advanced economies. This trend is depicted in figure 19 for advanced economies[11] and the case of the Euro area, the USA and the United Kingdom in figure 21. The evidence is in line with the results of Eber and Minoiu (2016) for the Euro area. They assess a banks' reluctance to adjust capital to stricter supervision, with a reduction in leverage mostly due to the shrinkage of assets rather than a rise in equity and a decrease in the supply of credit by fragile banks. The effects on the real economy are represented by the ratio of previous total lending to GDP. Figures 20 and 22 show the behaviour on advanced economies compared to total economies and a sample for the United States, Euro area, and the United Kingdom respectively. Ichiue and Lambert (2016) results show that regulatory tightening can explain about half of the decline in the foreign lending-to-GDP ratio between 2007 and 2013. Next paragraph will show that, while commercial banks were decreasing their support to the real economy, Multilateral Development Banks were increasing their lending activities.

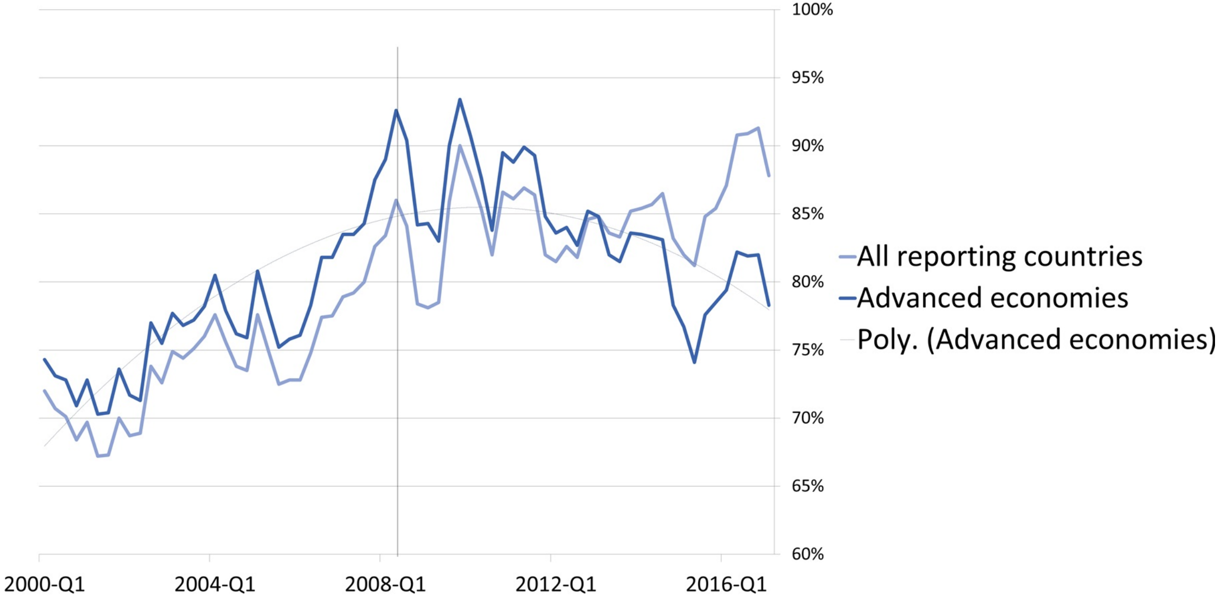
[11] Evidence on each country from all advanced economies can be found in the Appendix B 4.6.

Figure 19: Total credit from domestic banks to nonfinancial private sectors (market value) for advanced economies



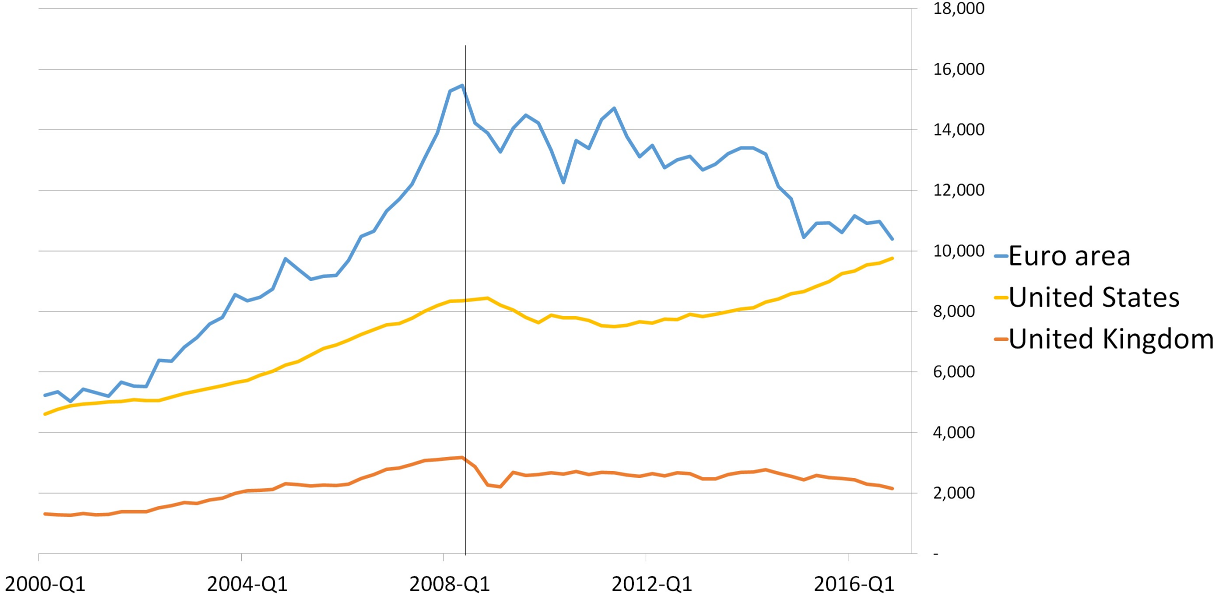
Source: authors elaboration of BIS total credit statistics from banks to private non–financial sector.

Figure 20: Total credit from domestic banks to nonfinancial private sectors as a percentage of GDP for advanced economies



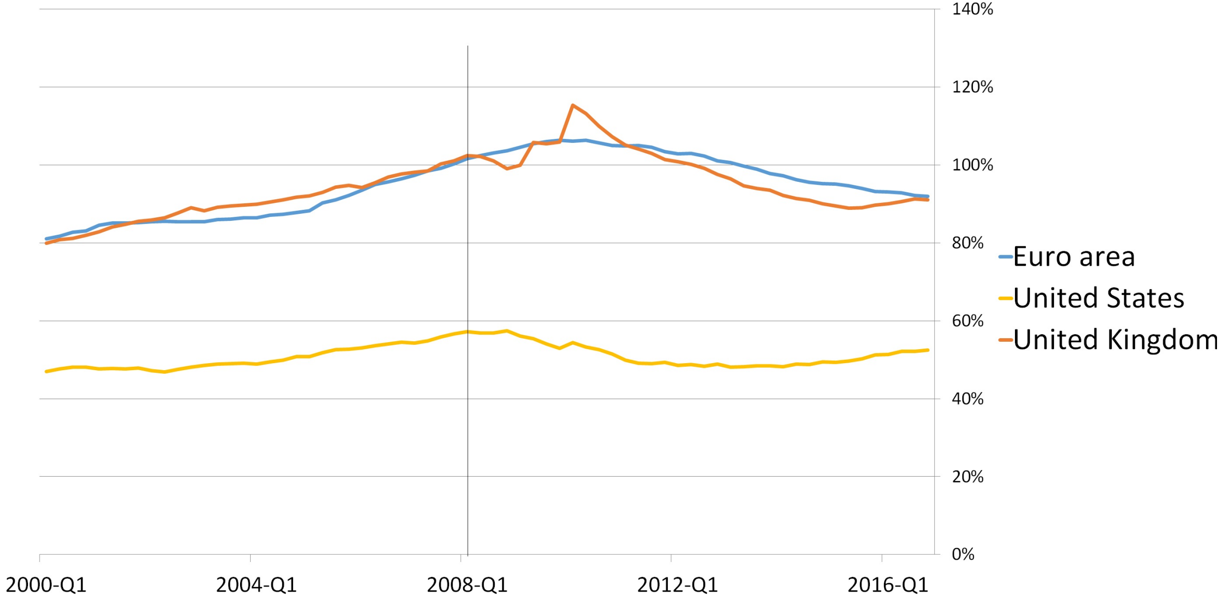
Source: authors elaboration of BIS total credit statistics from banks to private non–financial sector.

Figure 21: Total credit from domestic banks to nonfinancial private sectors (market value) for UK, USA and Euro area



Source: authors elaboration of BIS total credit statistics from banks to private non–financial sector.

Figure 22: Total credit from domestic banks to nonfinancial private sectors as a percentage of GDP for UK, USA and Euro area



Source: authors elaboration of BIS total credit statistics from banks to private non–financial sector.

4.4 The counter-cyclical role of MLIs into the economy

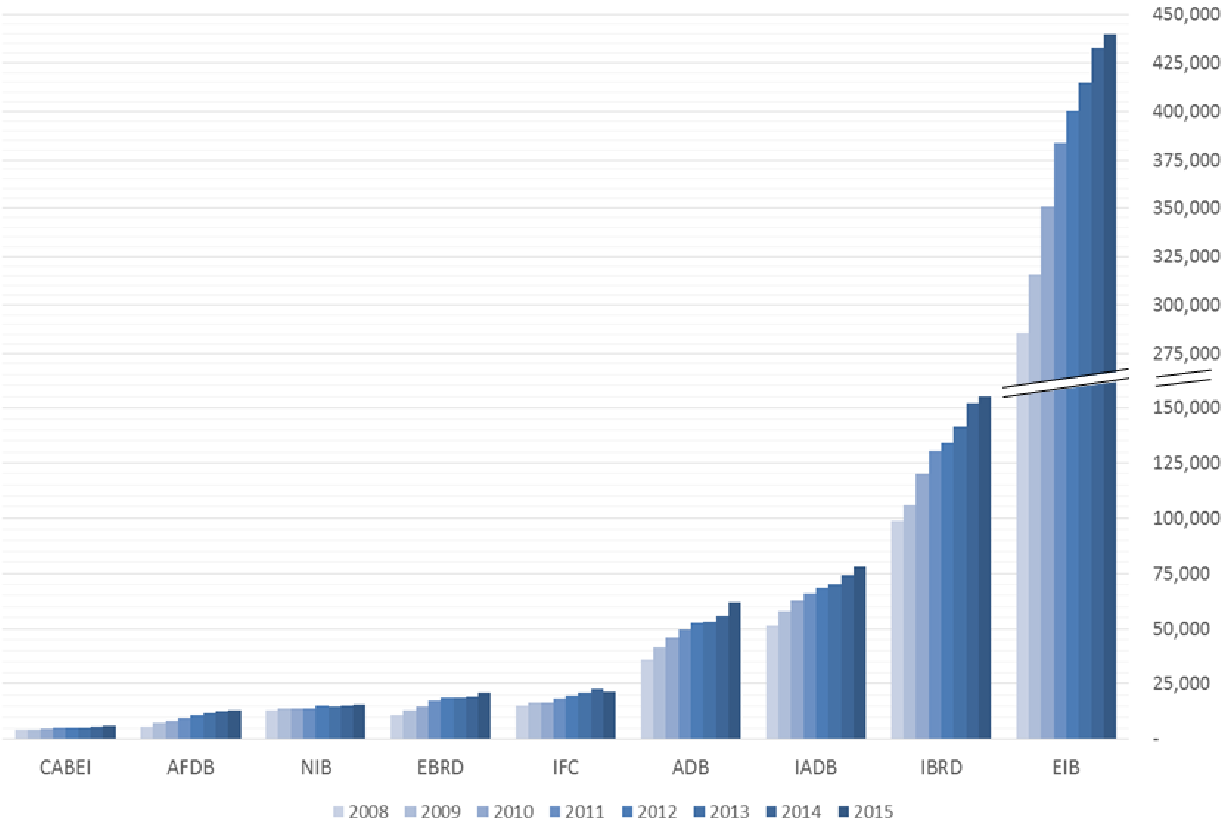
MLIs as public institutions are reckoned to have both an investments shaping and catalysing effect. Already back in the 90's, Bird and Rowlands (1997) remarked the potential pivotal role of International Financial Institutions (IFIs) especially for less developed countries and countries in transition that experienced external financing as an effective constraint on economic growth and development. For them, capital inflows could be used to overcome shortages of domestic saving thereby permitting higher levels of investment, as well as shortages of foreign exchange permitting larger quantities of imports. In his view, IFIs should configure not only as a direct source of multi-lateral assistance but also by influencing flows from other public and private sources.

Public Development Banks may have a positive effect in reducing the welfare costs of financial markets imperfections according to Eslava and Freixas (2016). Similarly, Mazzucato and Penna (2016) referring to State Investment Banks (SIBs) identifies four different roles in the economy: countercyclical, developmental, venture capitalist and challengeled. Its main finding is that, even though historically very often born after market-failure fixing, their role is market creating and shaping. A countercyclical role of IFIs into the economy is reckoned by Berensmann and Wolff (2014) not only by increasing funds for shock financing but also after a significant reform of their instruments. About a particular MDB, the EIB, Griffith-Jones and Tyson (2013) address policy lessons for developing countries as they seek finance for development in anti–cyclical financing, closing market gaps in long-term, low-cost and stable infrastructure lending. Ratha (2001) thesis is that multilateral loans tend to behave countercyclically concerning private flows to developing countries in the short term and to complement private flows in the medium term by signalling - and often fostering - a better investment environment in the borrowing country. MLIs are at the crossroad between public development banks and international financial institutions. Most MLIs increased their lending operations after the 2008 crisis to support investments in their countries of operation. According to S&P Global Ratings (2016), since 2008, supranationals outstanding debt has grown by a yearly average of 5%, to 1.2 trillion at end-2015 from less than 800 billion at end-2008. The 1.2 trillion represented 6% of global debt securities and close to 1.6% of the world's GDP at end-2015. MLIs countercyclical role can be recognised by the fact that there were two peaks of rated supranationals' debt growth when the economy was most demanding: in 2009, suddenly after the financial crisis of 2007-2008, by 16% and by 24% in 2012, when Greece was passing its most severe austerity package, the number of unemployed Europeans reached its highest ever level and the level of Spanish borrowing reached a record high.

We analyze S&P's report in order to retrieve a series of total loans in the balance sheet of MDBs over time. Figure 23 shows the evolution from years 2008 to 2015 of net loans in the portfolio assets of our sample of selected MDBs as reported by their balance sheet[12]. It can be noted an increasing trend of investments over the recent years.

[12]For graphical reasons IIC is not reported due to the small amount of its net loans (less than 1'000 USD bn).

Figure 23: Net loans (USD billions)



Source: authors elaboration of data from the collection in time of documents like S&P Global Ratings (2016).

4.5 MLIs regulation

Despite their enormous role in the worldwide economy and financial markets, MLIs are not regulated by an international regulatory framework, nor supervised. Historically this was not considered necessary for the founding members. These institutions do not have depositors and, de facto, MLIs benefit from a special regime compared to the regulation applicable to commercial banks worldwide reached by the Basel standards. MLIs have internal auditing processes, and their financial statements are externally audited. Nevertheless, there is not a common international framework aimed at assessing the financial strength of these institutions.

MLIs largely finance their lending activities by issuing bonds on the international capital markets, and they go through the assessment of their creditworthiness carried out by the Rating Agencies. Rating Agencies have their methodologies which combine quantitative factors and qualitative drivers that lead to a final rating taken as a reference by MLIs' bondholders in their investment decisions.

Given the role of the MLIs in the developed and developing economies and their growing systemic importance, common industry standards on how to evaluate MLIs financial strengths might be desirable[13]. In a "mild ambition" scenario, this could be achieved by the MLIs themselves beyond the existing efforts (e.g., COMPAS, Common Performance Assessment System; this is a consolidated source of data on how MDBs are contributing to positive development results born in 2006. The Common Performance Assessment System or COMPAS is a self-reporting exercise through which MDBs track their capacities to manage for development results by measuring with key performance indicators MDBs' capacity to apply and improve operational processes toward achieving results on the ground. Data are provided in seven categories: country-level capacity development, performance-based concessional financing, results-based country strategies, projects and programs, monitoring and evaluation, learning and incentives, and interagency harmonization. MDBs hope that this system will improve accountability[14] and GATS, General Agreement on Trade in Services[15]). In a more ambitious scenario, a newly created oversight body should be responsible for defining common regu-

[13]See the interesting legal point of view of Cottier and Krajewski (2010).

[14]See more in Bhargava (2006) and at the webpage www.mfdr.org/Compas/index.html.

[15]See more at https://www.wto.org/english/docs_e/legal_e/26-gats.pdf.

latory rules applicable to MLIs given their specificities and be accountable for the supervision of the MLIs. Currently, there are no evident needs for such solution (e.g., from MLIs' bond investors), but in the era of financial complexity, prevention is better than cure.

4.6 Concluding remarks

We retrieve some publicly available data on Multilateral Development Banks (MDBs), their ratings, and their lending in latest years. We compare them with the aggregated data from BIS consolidated total credit statistics from tear 2000 to year 2016. More specifically, data are BIS long series on total credit, at quarterly frequency, from the Lending sector *Banks, domestic* to the Borrowing sector *Private non-financial sector*. The data reveal that commercial banks that have shrunk their lending in most advanced economies in the considered time framework. On the contrary, Multilateral Lending Institutions are increasingly supplying credit to the economy. MDBs finance socially desirable projects in their member states and abroad. The financing methods they apply are becoming more diversified (but mainly through bonds) while their funding increases.
Although there is enough control over project financing, both for projects social goal and their value assessment, there is no unified international regulation able to provide to MDBs a supervision. We find that this lack bypasses MLIs increasing systemic importance and interconnection worldwide. While the traditional banking sector is supervised to ensure a proper risk evaluation and sound capital and liquidity buffers in case of financial distress, there is no analogous supervisory control on such huge banks, that, in most cases, cannot even rely on callable shareholders capital. We challenge if the annual credit rating assessment of MDBs by the Credit Rating Agencies is enough to guarantee financial markets stability or a unified regulatory hat would be desirable. In this case, the main effort would be to render MDBs and all the other financial institutions comparable regarding reporting and regulatory methodology. It will be not an easy task for the legislator, since MDBs have specificities, e.g., in terms of portfolio concentration.

Appendix A.

Main description of the MDBs analysed

AfDB (1964) (African Development Bank)
Its main purpose is to promote sustainable economic growth and reduce poverty in Africa. Historically, the bank has pursued these goals primarily by setting medium- and long-term loans for public-sector projects; however, its focus on private-sector lending has increased. The bank also makes equity investments and provides a variety of financial and technical advisory services. AfDB also provides development finance on concessional terms to its low-income member countries that are unable to borrow on the above non–concessional terms. Money for such loans comes from the 24 nonregional shareholders in the form of grant contributions. At the end of 2015, its net loans amounted to 13'066 USD billions.

ADB (1966) (Asian Development Bank)
It is owned by its 65 members, 47 from the region and 18 from other parts of the globe. ADB's mission is to help its developing member countries reduce poverty and improve their quality of life. Special consideration is given to smaller and less-developed countries and projects that foster regional economic growth. It provides loans, technical assistance, guarantees, grants and equity investments that promote the economic and social advancement of its members and to encourage public and private sector investment for development purposes. At the end of 2015, its net loans amounted to 61'941 USD billions.

CABEI (Central American Bank for Economic Integration)
Its main purpose is to promote intraregional cooperation and economic growth and development among the countries of Central America. Its focus is on projects, particularly public-sector infrastructure projects. CABEI's small equity investments are predominantly in investment funds. At the end of 2015, its net loans amounted to 5'905 USD billions.

EBRD (1991) (European Bank for Reconstruction and Development)
It is owned by 60 countries and 2 intergovernmental institutions, the European Union and the European Investment Bank. EBRD's charter is unique among MDBs in that it stipulates that EBRD may work only in countries that are committed to democratic principles. It fosters the transition to market economies by the Central and Eastern European and CIS

countries by promoting private and entrepreneurial initiatives. EBRD pursues these objectives principally by lending (primarily to the private sector and to public-sector projects supporting the private sector), making equity investments, and providing guarantees. EBRD's share capital is provided by its members. EBRD does not directly use shareholders capital to finance its loans. Instead, its triple-A creditworthiness rating enables it to borrow funds in the international capital markets by issuing bonds and other debt instruments at highly favourable market rates. Although its shareholders are in the public sector, EBRD invests mainly in private enterprises, usually together with commercial partners. At the end of 2015, its net loans amounted to 21'073 USD billions.

EIB (1958) (European Investment Bank)
Its shareholders are the 28 EU member states. Its main purpose is to help finance balanced economic development in EU member states. The bank provides loans and guarantees to public- and private-sector borrowers for capital investment projects, mainly in industry, energy, and the environment. It also lends to EU candidate countries to support their accession processes and to other non-EU countries in accordance with the EU's cooperation and development policies. At the end of 2015 its net loans amounted at 439'865 USD billions.

IADB (1959) (Inter-American Development Bank)
It is the oldest of the regional development banks. It is owned by its 47 member countries, which include 26 Latin American and Caribbean states, the United States, Canada, 16 European countries, Israel, the Republic of Korea, and Japan. Its purpose is to accelerate economic and social development in Latin American and Caribbean countries, with an emphasis on poverty reduction and social equity, modernization and sector reform, economic integration, and the environment. In support of these objectives, the bank provides long-term financing at favorable interest rates to governments, other public-sector entities, and a limited number of private-sector borrowers. It also provides technical and advisory services to enhance the efficiency and transparency of public institutions and supports regional initiatives by producing information and knowledge for policy discussion and funding technical cooperation to strengthen regional integration. At the end of 2015, its net loans amounted to 78'301 USD billions.

IBRD (International Bank for Reconstruction and Development, World Bank Group) (1945)
IBRD is the largest constituent of the World Bank Group. The World Bank Group, which is headquartered in Washington, D.C., is made up of five institutions: the International Bank for Reconstruction and Development, the International Development Association, the International Finance Corporation, the Multilateral Investment Guarantee Agency, and the International Center for Settlement of Investment Disputes. Each institution plays a different but important role in the group's corporate mission of reducing global poverty and improving living standards in the developing world. Together, they provide low-interest loans, interest-free credit, and grants to governments and the private sector in developing countries for investments in education, health, infrastructure, communications, and many other purposes, as well as services in support of those investments. The International Bank for Reconstruction and Development focuses on middle income countries and creditworthy low income countries to reduce poverty by promoting sustainable economic development via loans, guarantees, and related assistance for projects and programs in its developing member countries. It lends only to governments, financing these loans primarily by selling triple-A-rated bonds in the world's financial markets. At the end of 2015, its net loans amounted to 155'040 USD billions.

IIC (Inter-American Investment Corporation)
Its main purpose is to promote the economic development of its Latin American and Caribbean member countries by financing small and midsize enterprises (SMEs) without government guarantees. This is achieved by providing loans and guarantees, making equity investments, mobilizing funding from other lenders and providing advisory services. At the end of 2015, its net loans amounted to 925 USD billions.

IFC (International Finance Corporation, World Bank Group)
IFC focuses on financing private sector projects, in which it may take an equity stake in addition to lending, to support economic growth and development by providing loans without government guarantees and making equity investments in private entities. IFC also acts as a catalyst through its co-financings, syndications, securitizations, underwritings, and guarantees, and as a technical and financial advisor, including acting as an asset manager. At the end of 2015, its net loans amounted to 21'336 USD billions.

NIB (Nordic Investment Bank)

Its main purpose is to promote sustainable economic growth in member countries via long-term financing for private and public projects. NIB also finances projects in emerging markets outside member countries that are of mutual interest to member and borrowing countries. At the end of 2015, its net loans amounted to 15’627 USD billions.

Appendix B.

Total credit from domestic banks to nonfinancial private sectors (market value) for other advanced economies

Source: authors elaboration of BIS total credit statistics from banks to private non–financial sector.

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Publications

- M. Bonollo, I. Crimaldi, A. Flori, L. Gianfagna, F. Pammolli, "Assessing financial distress dependencies in OTC markets: a new approach using Trade Repositories data", in *Financial Markets and Portfolio Management*, Springer, vol. 30, issue 4, pp. 397–426, 2016.
- L. Gianfagna, "Rating and pricing: state of the art for the proposal of new methodologies", in *Proceedings of Finance and Economics Conference*, Munich, Germany, 2014.
- E. Ferra, L. Gianfagna, "The role of Institutions and culture for fragile firms in Bosnia-Herzegovina", in *Proceedings of the 4th Annual Research Conference Global Business, Emerging Markets and Human Rights*, Maastricht School of Management (MSM), Maastricht, The Netherlands, 2014.

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- L. Gianfagna, "Finance and Economics Conference 2014", at *Lupcon Centre for Business Research*, Munich, Germany, 2014.
- E. Ferra, L. Gianfagna, "4th Annual Research Conference Global Business, Emerging Markets and Human Rights", at *Maastricht School of Management (MSM)*, Maastricht, The Netherlands, 2014.

Working Papers

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I, the Undersigned Andrea Flori, born in Siena (july 11, 1986) do hereby declare that the article:

“**Assessing financial distress dependencies in OTC markets: a new approach using trade repositories data**” (DOI 10.1007/s11408-016-0275-7), published in the journal *Financial Markets and Portfolio Management* (Springer, 30: 397-426, 2016) and reported also in my Doctoral Thesis (“*Three Essays on Systemic Risk and Financial Stability*”, Imt Lucca),

was jointly prepared with co-authors Michele Bonollo, Irene Crimaldi, Andrea Flori, Laura Gianfagna, and Fabio Pammolli. I authorize, therefore, Laura Gianfagna to use the aforementioned article in her Doctoral Thesis.

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