The Impact of European Regulatory Measures on Financial Analysts‘ Behaviour and Information Environment

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Vorwort

Die vorliegende Arbeit entstand während meiner Zeit als wissenschaftlicher Mitarbeiter und Doktorand an der Professur für Rechnungslegung und Wirtschaftsprüfung der Georg-August-Universität Göttingen und wurde im Sommersemester 2017 von der Wirtschaftswissenschaftlichen Fakultät der Georg-August-Universität Göttingen als Dissertation angenommen.

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Göttingen, im August 2017 Philipp Löw

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"Analysts are supposed to be a check on the financial system—people who can wade through a company's financials and tell investors what's really going on. (…) *Unfortunately, some are little more than cheerleaders—afraid of rocking the boat at their firms, afraid of alienating the companies they cover and drawing the wrath of their superiors."*[1]

1. Introduction

1.1 Context of the dissertation

This quotation by the well-known financial analyst Mike Mayo summarises some of the main points of the criticism about sell-side equity analysts which has been discussed in literature since the 1990s (see, e.g., Demski 2003; Mehran and Stulz 2007; Ramnath et al. 2008; Bradshaw 2011, for overviews).[2] Sell-side equity research is conducted by financial analysts employed by brokerage houses and investment banks and is provided for customers of these financial institutions (Michaely and Womack 1999, pp. 657-659; Groysberg and Healy 2013, pp. ix, 47-58). By mitigating information asymmetries and by providing insight for their customers, who can be institutional and retail investors, sell-side analysts act as information intermediaries and also support the companies they cover by increasing the investor recognition of the covered stocks (Healy and Palepu 2001, p. 408; Groysberg et al. 2008, p. 26; Bowen et al. 2008; Groysberg and Healy 2013, pp. ix, 20f.; Li and You 2015). Typically, sell-side analysts compile, besides textual analysis in their written research reports, three different common quantitative measures: earnings forecasts, target prices and stock recommendations (Brav and Lehavy 2003, p. 1933; Asquith et al. 2005, p. 255; Demirakos et al. 2010, p. 37; Bradshaw et al. 2013, p. 931). However, prior research has provided evidence that these

[1] Mayo (2011).
[2] Mike Mayo is the author of the book "*Exile on Wall Street: One Analyst's Fight to Save the Big Banks from Themselves*" published in 2011.

measures can be optimistically biased by conflicts of interest (e.g., Demski 2003; Mehran and Stulz 2007; Ramnath et al. 2008; Bradshaw 2011, for overviews).[3]

Conflicts of interest caused by economic incentives for the financial analysts can reduce their effectiveness as information intermediaries and thus can cause the persistence of information asymmetries (Healy and Palepu 2001, p. 409, 433; Ramnath et al. 2008, p. 57). Two categories of conflicts of interest especially are closely related to the business models of investment banks and brokerage houses, which typically use the income generated in the investment banking departments and trade commissions to fund their sell-side financial analysts, since many customers do not compensate sell-side research departments directly for the provision of their reports (Cowen et al. 2006, pp. 122-124; Ljungqvist et al. 2007, p. 421; Groysberg and Healy 2013, pp. 47-57; Bilinski et al. 2015, p. 2).[4]

First, in investment banks, sell-side financial analysts could be pressured to make biased research reports about customers of their employers' securities underwriting or M&A departments in an overly optimistic direction, in order to support the business of these units (Karamanou 2011, p. 2; Bradshaw 2011, p. 26). Second, sell-side financial analysts have an incentive to publish overly optimistic research in order to maintain good relations with the covered firm's management, which should increase the probability of receiving "*privileged access*" (Carapeto and Gietzmann 2011, p. 757) to the firm's information (Karamanou 2011, p. 2; Bradshaw 2011, p. 26).[5] However, such analysts, who might use information obtained in

[3] Demski (2003, p. 61) draws the conclusion that a "*general finding is that analysts' forecasts are upward biased*", and that "*recommendations are also typically skewed toward the 'strong buy' and 'buy' categories, rather than to 'hold' or 'sell'* ". Thus, I define, in line with relevant prior literature (e.g., Ramnath et al. 2008; Mehran and Stulz 2007), that over-optimism is caused by conflicts of interest in the sense of biased advice. Moreover, it is important to note, that "*an important distinction between biased forecasts driven by judgment errors as distinct from economic incentives is that the former is non-motive driven, while the latter is motive driven*" (Ramnath et al. 2008, p. 57).

[4] Consequently, Groysberg and Healy (2013) name the business models as the "*investment banking model*" (Groysberg and Healy 2013, p. 59) and the "*trading commission model*" (Groysberg and Healy 2013, p. 74).

[5] Bradshaw (2011, pp. 26-28) ranks the sources of conflict of interest for financial analysts according to their relative importance in the literature (descending order): 1. Investment banking business, 2. Maintaining the favour of firm managers, 3. Trade volume generation, 4. The influence of institutional investors, 5. Hired analyst coverage, 6. Behavioural bias of analysts. As, for instance, Groysberg and Healy (2013, pp. 89-91) point out, that trade volume generation is another relevant source of conflict of interest for brokerage firms applying the "*trad-*

many cases, via selective disclosures, can improve the informativeness of their research outputs and the accuracy of their earnings forecasts (e.g., Gintschel and Markov 2004; Hutton 2005; Mohanram and Sunder 2006). Thus, it is not unambiguously defined how financial analysts with "*privileged access*" (Carapeto and Gietzmann 2011, p. 757) use this competitive advantage (Michaely and Womack 1999, p. 656; Bradley et al. 2003, p. 3).

While issuing stock recommendations can be seen as the final step in the financial analysts' research process summarizing the insights of analysts' information processing, the common quantitative metrics are also being issued separately from each other (Beyer et al. 2010, p. 325; Bradshaw 2009, p. 1076; Booth et al. 2014, p. 465; Asquith et al. 2005, p. 255). Moreover, there is growing evidence from recent research, that sell-side financial analysts use earnings forecasts, target prices and stock recommendations in different ways (Malmendier and Shanthikumar 2014; Bilinski et al. 2015). Malmendier and Shanthikumar (2014) provide evidence that analysts have a stronger incentive to make biased stock recommendations than earnings forecasts. This is because overly optimistic earnings forecasts are negatively welcomed by both the management of the covered firms and by the institutional investors (Malmendier and Shanthikumar 2014, p. 1289). Bilinski et al. (2015) can show that financial analysts concentrate on biasing the more granular target prices instead of stock recommendations or earnings forecasts. Thus, these recent findings affirm overall evidence in prior research that a positive bias in earnings forecasts, caused by conflicts of interest, is less clear (Mehran and Stulz 2007, p. 287).

Both outlined business models for funding analyst sell-side research were challenged by different regulatory reforms in the US and the European Union, which addressed conflicts of

ing commission model" for funding equity research. Analysts employed by such brokerage firms could be pressurised into biasing their reports because optimistic research reports generate a higher trading volume and thus higher commission for their employer than pessimistic ones (Karamanou 2011, p. 2; Groysberg and Healy 2013, pp. 89-90). Another relevant conflict of interest which could create incentives for biasing research reports are relations with institutional investors (e.g., Bilinski et al. 2015). However, these conflicts of interest are not addressed by the regulations outlined in this section and thus might persist even after the introduction of the regulatory reforms (Cowen et al. 2006, p. 120; Bilinski et al. 2015, p. 5).

interest in analyst research and selective disclosures (Avgouleas 2005; Groysberg and Healy 2013; Dubois et al. 2014). While the US-regulatory measures NYSE Rule 472, NASD Rule 2711, Regulation Analysts Certification (Reg AC) and the Global Settlement concentrate on rules for the disclosure and prevention of conflicts of interest in investment research, Regulation Fair Disclosure (Reg FD) concerns the prevention of selective disclosures (e.g., Contoudis 2003; Hovakimian and Saenyasiri 2010; Koch et al. 2013; Hovakimian and Saenyasiri 2014). In the European Union, conflicts of interest in analysts' research are addressed by two directives, the MAD (Market Abuse Directive, introduced in 2003) and the MiFID (Markets in Financial Instruments Directive, introduced in 2004) (e.g., Ferrarini 2004; Enriques 2006). According to Christensen et al. (2016), a remarkable feature of the MAD is that substantial differences exist across the EU member countries concerning the time of implementation and the severity of the sanctions.

The MAD and the MiFID are, amongst other objectives, geared up for the mitigation of conflicts of interest in the field of the financial analysts' investment research (MiFID, recital 29; MAD, Article 6(5)), by, in the case of the MAD, introducing disclosure rules and by introducing and strengthening organisational requirements (e.g., so-called "*chinese walls*") and conduct-of-business rules for brokerage firms and banks in the case of the MiFID (e.g., Avgouleas 2005; Enriques 2006). Both directives are accompanied by implementing directives (Commission Directive 2003/125/EC and Commission Directive 2006/73/EC), which contain detailed regulations concerning the presentation of financial research and the prevention and disclosure of possible conflicts of interest.

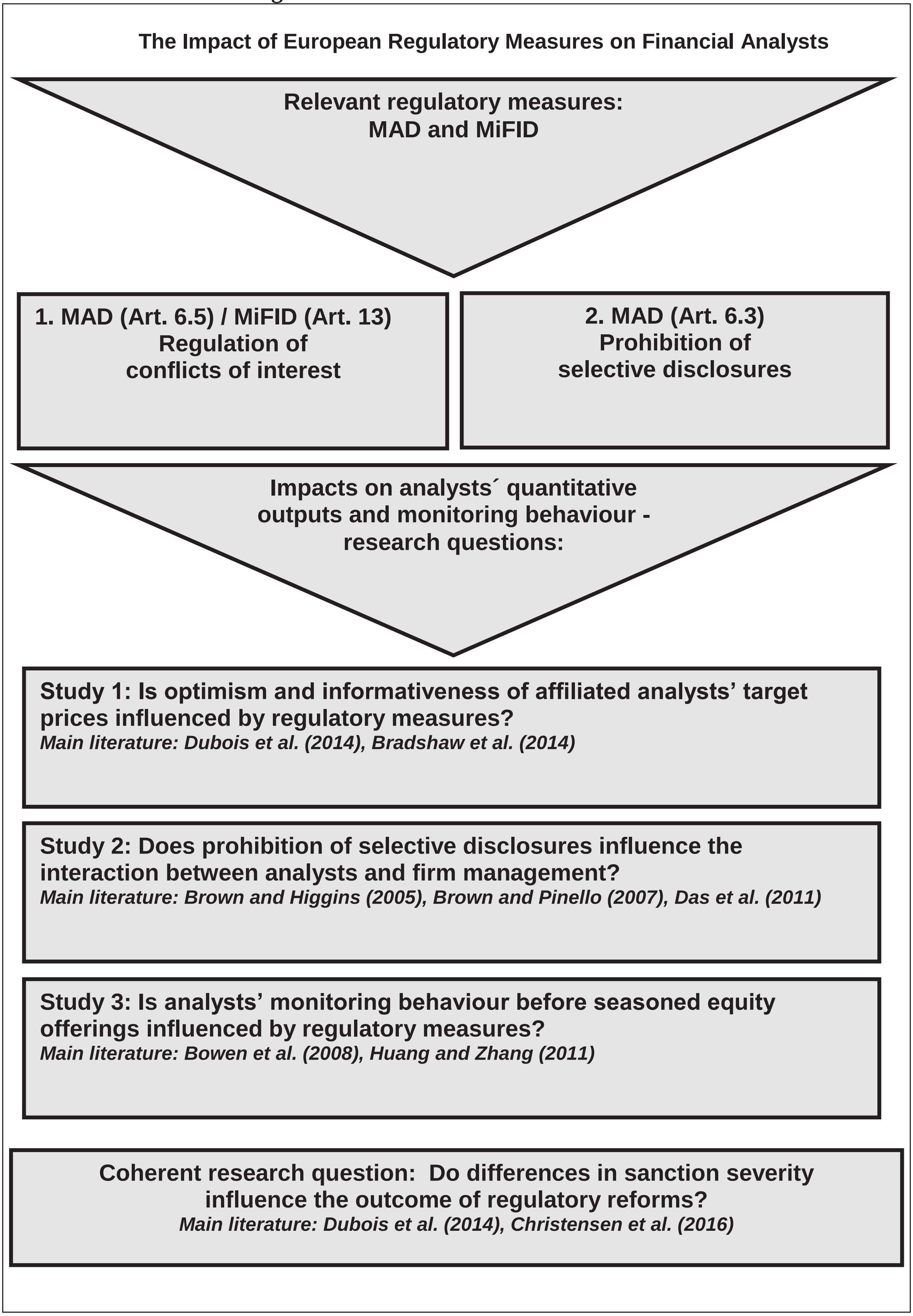
Moreover, the MAD prohibits the issuance of selective disclosures (e.g., Ferrarini 2004). According to Article 6(3) of the MAD, firms are required to disclose insider information to all market participants and are not allowed to disclose insider information to only selected individual financial analysts, which makes the MAD comparable to Reg FD, the relevant US regulatory measure regarding the prohibition of selective disclosures (Avgouleas 2005; Lau Hansen and Moalem 2009).

1.2 Contribution of the dissertation

The European regulatory environment provides, from a researcher's point of view, an ideal setting for investigating the impacts of regulatory changes, since the staggered implementation of the MAD across EU-Member countries facilitates the identification of regulatory effects (Christensen et al. 2016). Moreover, the substantial differences across the EU member countries concerning the severity of the sanctions of the MAD allow to investigate whether these differences influence regulatory outcomes (Dubois et al. 2014; Christensen et al. 2016). Utilising these advantages of the European regulatory setting, this dissertation investigates whether the objectives of the outlined European measures MAD and MiFID were met by investigating their impact on the behaviour and information environment of sell-side financial analysts. Furthermore, although the relevant regulatory measures in the US and Europe are comparable to each other (Avgouleas 2005, p. 211; Dubois et al. 2014, p. 496), additional insights going beyond the prior investigations of the US regulatory measures (e.g., Cornett et al. 2007; Kadan et al. 2009; Das et al. 2011) can be gained by considering the potential differences in the institutional setting between the US and Europe and by including additional analyst metrics such as target prices.

As outlined in Figure 1.1, I investigate the impact of the regulation of conflicts of interest and prohibition of selective disclosures on sell-side financial analysts´ quantitative outputs and monitoring behaviour, using all three common quantitative measures: earnings forecasts, target prices and stock recommendations. My investigation is split up into three different empirical studies, each addressing another specific research question within the scope outlined.

Figure 1. 1: Contribution of the Dissertation



Study 1 investigates the question whether optimism and informativeness of target prices issued by sell-side analysts, whose employing financial institution acted as securities underwriter or M&A advisor for a covered firm ("*affiliated analysts*")[6], were influenced by the European regulatory measures. As pointed out, Bilinski et al. (2015), provided evidence that sell-side financial analysts concentrate on biasing the more granular target prices instead of stock recommendations or earnings forecasts. Moreover, the disclosure requirements of the MAD are geared more explicitly towards stock recommendations, making target prices a less visible measure for sending an overly optimistic opinion in the post-regulation period.[7] Thus, the regulatory measures introduced could provoke a trade off between the quantitative analyst metrics. Concentration on biasing target prices could be seen as an "*avoidance strategy*" (Leuz and Wysocki 2016, p. 536). By addressing this research question, Study 1 augments prior literature in several dimensions. First, the related study of Dubois et al. (2014) concentrates on stock recommendations, which, based on the results of Malmendier and Shanthikumar (2014), are considered to be the more biased measure compared with earnings forecasts. A recent, and growing, stream of literature focuses on analysts' target prices which, when compared with discrete stock recommendations, contain more forthright valuation implications (Bradshaw et al. 2013). Thus, Study 1 augments prior literature by examining the impact of the regulatory measures on target prices and reacts, like the studies of Bilinski et al. (2013), Bradshaw et al. (2014) and Bilinski et al. (2015) to the call for more research by Ramnath et al. (2008, p.68), who state, that "*further research is required to describe the behavior of the forecasts that have higher price impacts, such as long-term growth forecasts and target prices*". Second, while Dubois et al. (2014) and Hovakimian and Saenyasiri (2014)

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[6] Typically, financial analysts are considered to be affiliated, when their employing bank or brokerage firm was involved as an underwriter or advisor in an IPO, SEO or M&A transaction of the covered firm (e.g., Kolasinski and Kothari 2008; Kadan et al. 2009; Dubois et al. 2014).

[7] Article 6(4) of Directive 2003/125/EC requires banks and brokerage firms employing analysts to disclose, separately and with a quarterly frequency, tables which include the distributions of all their unaffected and their conflicted buy/hold/sell recommendations. However, there is no comparable disclosure requirement for target prices (Staikouras 2008, p. 370).

investigate the impact of the MAD on financial analysts’ conflicts of interest, there is, to my knowledge, apart from the studies of Prokop and Kammann (2017), who investigate earnings forecasts, and Höfer and Oehler (2014), who apply mean comparison tests, no study which applies multivariate analysis in order to investigate the impact of the MiFID on stock recommendations and target prices. Thus, Study 1 contributes to the existing literature on the regulation of financial analysts by examining the effects of the MiFID on stock recommendations and target prices.

Study 2 analyses whether the prohibition of selective disclosures introduced by the MAD influences the interaction between sell-side analysts and the management of the covered firms. This interaction between analysts and firm management is known as “*forecast guidance*” or “*expectations management*” in the literature (e.g., Matsumoto 2002; Cotter et al. 2006). As pointed out, sell-side analysts are interested in good relations with a covered firm’s management, which is why they pay attention to maintaining their earnings forecasts on a moderate level shortly before the earnings announcement date because the management has an incentive “*to meet or beat*” financial analysts’ earnings forecasts (e.g., Degeorge et al. 1999; Bartov et al. 2002, p. 202; Wallmeier 2005). After the introduction of the MAD, private forecast guidance conducted via selective disclosures by firm management is no longer allowed, thus guidance has to be conducted publicly, which should make it more difficult for firms to achieve a positive stock price benefit by using expectations management (Avgouleas 2005, p. 211; Canace et al. 2010; Williams and Sun 2011). Thus, study 2 investigates how the introduction of the MAD influenced the prevalence of expectations management. By doing this, Study 2 augments prior literature by addressing how regulatory changes and cross-country differences could influence the amount of expectations management which is applied by firms. Thus, Study 2 adds to the stream of literature on forecast guidance (e.g., Brown and Higgins 2005; Brown and Pinello 2007; Das et al. 2011).

Study 3 investigates, whether affiliated sell-side financial analysts' monitoring behaviour before seasoned equity offerings (SEOs) is influenced by the introduction of the MAD and MiFID. Prior research (e.g., Altınkılıç and Hansen 2003; Corwin 2003; Mola and Loughran 2004; Bowen et al. 2008; Huang and Zhang 2011) provides evidence, that shares in an SEO have to be issued with a discount, which increases the cost of issuing equity capital (e.g., Bowen et al. 2008). The study by Bowen et al. (2008) provides evidence that this discount can be reduced, when issuing firms are covered by affiliated analysts who work for the main underwriter of the SEO. These analysts should have "*privileged access*" (Carapeto and Gietzmann 2011, p. 757) to company information due to their employers' involvement in the marketing of the SEO and the due diligence investigations (Michaely and Womack 1999, p. 656; Bradley et al. 2003, p. 3; Bowen et al. 2008, p. 666). Thus, in the very specific SEO-setting, affiliated analysts can help to reduce information asymmetries utilizing the information obtained via their employers' involvement in the SEO (Bowen et al. 2008). However, the regulatory measures geared up to prevent "*privileged access*" (Carapeto and Gietzmann 2011, p. 757) to firm information could stop this effect of affiliated analyst coverage in the context of SEOs, which could be seen as an "*unintended consequence*" (Brüggemann et al. 2012; Leuz and Wysocki 2016, p. 531) of the introduction of MAD and MiFID. By addressing this research question, Study 3 augments the prior findings in the SEO underpricing literature (e.g., Corwin 2003; Mola and Loughran 2004; Bowen et al. 2008; Huang and Zhang 2011). Study 3 is, to my knowledge, the first one to investigate how analyst coverage influences SEO underpricing in an international cross country setting. Bowen et al. (2008) and Huang and Zhang (2011) investigate the impact of analyst coverage for samples of US-SEOs, while Gupta et al. (2013), who examine the impact of regulatory differences on SEO underpricing, do not include analyst coverage as an explanatory variable in their international sample of SEOs from 39 countries. Moreover, the SEO underpricing setting provides an accurate direct measure for the cost of capital, in contrast to indirect measures like bid-ask spreads or estimated discount rates obtained from valuation models (Bowen et al. 2008, p. 662). In addition to this advantage, SEO underpricing should be less affected by endogeneity issues, since it is measured after the number of covering analysts is determined and over a short time interval of just one day (Bowen et al. 2008, p. 662).

A coherent research question, addressed by all three studies, is whether differences in sanction severity influence the outcome of regulatory reforms. Investigating this research question is fascilitated by the ideal features of the European regulatory environment, which includes differences in sanctions severity for infringements of the regulatory measures between EU member countries (Dubois et al. 2014; Christensen et al. 2016). Thus, by exploiting the "*cross-sectional variation*" (Leuz and Wysocki 2016, p. 571) in sanction severity of the MAD as well as by exploiting the outlined "*time-series variation*" (Leuz and Wysocki 2016, p. 571) in the MAD implementation across EU member countries, this dissertation adds to the growing stream of literature investigating the impact of regulatory changes on the basis of the European regulatory environment (e.g., Christensen et al. 2013b; Dubois et al. 2014; Christensen et al. 2016).

1.3 Content of the dissertation

The dissertation is organized as follows: The introduction (Chapter 1) outlines the context, contribution, and structure of the dissertation. Chapter 2 includes a portrayal of the relevant regulatory measures and provides implications for the empirical investigation. The following three chapters, chapters 3 to 5, include the three empirical studies. The final chapter 6 draws a conclusion by summarising the main findings of the empirical studies, by outlining the main limitations and by presenting potential avenues for further research.

Chapter 3: Analysts' Conflicts of Interest - The Impact of MAD and MiFID on Target Prices:

Study 1 investigates the impact of the introduction of the MAD and MiFID on the optimism and informativeness of analysts' target prices for a sample of firms listed in 13 EU member countries. As in Dubois et al. (2014), the study concentrates on one important conflict of interest, which is addressed by Article 6 (1(d)) and Article 6 (1(e)) of Commission Directive 2003/125/EC, the impact of securities underwriting and M&A advisory activities on affiliated analysts, who are employed by banks or brokers providing these services to the firms that are covered. As a first step, I replicate the baseline model of Dubois et al. (2014) in order to validate my affiliation identification approach. As in Dubois et al. (2014), my results show that the MAD had a mitigating impact on over-optimism in affiliated analysts' stock recommendations. Concerning optimism in target prices, I find a highly significant positive impact of the regulatory measures MAD and MiFID on the target price optimism of affiliated analysts. Thus, my results provide evidence that analysts use their quantitative metrics in different ways. These results imply that target prices are an eligible measure for sending overly optimistic signals to investors in the post-regulation period. Moreover, I cannot find a reduced informativeness of affiliated target price revisions in the post-regulation period, which implies that market participants cannot see through the incentives of affiliated analysts properly since they do not discount target price revisions thoroughly.

Chapter 4: The Impact of the MAD on Expectations Management:

Study 2 concentrates on investigating how the introduction of the MAD influenced the prevalence of expectations management of firms listed in 13 EU member countries. The results provide evidence that the MAD did not have a significant constraining impact on the amount or incidence of expectations management. Moreover there is at least some evidence that severe sanctions and extensive competences for regulatory authorities do increase the mitigating impact of the MAD on expectations management.

Chapter 5: Affiliated Analyst Coverage and SEO Underpricing - The Impact of MAD and MiFID:

Study 3 investigates whether the MAD as well as the MiFID reduce the effectiveness of coverage by affiliated analysts in the context of seasoned equity offerings (SEOs) for a sample of SEOs by firms listed in 13 countries within the European Union. The results of Study 3 provide evidence for a reduced effectiveness of affiliated coverage in reducing SEO underpricing after the introduction of the MAD and the MiFID. Thus, after the introduction of the regulatory measures, the competitive advantage of affiliated analysts vanishes. However, the results are partly driven by new firms, which did not issue equity capital before the year 2008, as shown in one of the tests for robustness. Moreover, my results provide evidence that differences in sanction severity and supervisory power concerning the MAD between the sample countries do not have an impact on underpricing of treated SEOs in the post-treatment period.

2. Regulation of Financial Analysts' Investment Research in the European Union

2.1 Objectives of the regulatory reforms

With two directives, the MAD (Market Abuse Directive, introduced in 2003) and the MiFID (Markets in Financial Instruments Directive, introduced in 2004), the European Union regulates financial analysts' investment research (e.g., Ferrarini 2004; Enriques 2006).[8] Both directives are accompanied by implementing directives (Commission Directive 2003/125/EC for the MAD and Commission Directive 2006/73/EC for the MiFID), which contain detailed regulations concerning the conflicts of interest of financial analysts in investment research.[9] Moreover, the MAD, MiFID and the accompanying implementing directives had to be transposed into national law by EU-Member countries in order to become applicable.[10] The MAD requires the introduction of rules for producers of analyst investment research reports in order to "*take reasonable care to ensure that such information is fairly presented and* [that the producers] *disclose their interests or indicate conflicts of interest concerning the financial instruments to which that information relates*" (MAD, Article 6(5)). Moreover, the MAD is geared up for the prevention of selective disclosures, which could be provided for a limited number of financial analysts by firms (e.g., Avgouleas 2005, p. 211), since "*prompt and fair disclosure of information to the public enhances market integrity, whereas selective disclosure by issuers can lead to a loss of investor confidence in the integrity of financial markets*" (MAD, recital 24).

With regard to the prevention of conflicts of interest, the MiFID states: *"The expanding range of activities that many investment firms undertake simultaneously has increased*

[8] Beginning in 2016 new directives (MAR, MiFID 2) become applicable, which replace the MAD and MiFID. Detailed information concerning implementation dates of the directives is available on the website of the European Commission.
[9] I use the terms bank and brokerage firm, when referring to institutions, which employ financial analysts and provide investment banking services such as underwriting and M&A advisory. The corresponding term in the relevant Commission Directive 2003/125/EC, the MiFID and Commission Directive 2006/73/EC is investment firm. However, analyst research can also be produced by credit institutions or independent analysts (Commission Directive 2003/125/EC, Article (1)).
[10] See MAD, Article 18; Commission Directive 2003/125/EC, Article 10; MiFID, Article 70; Commission Directive 2006/73/EC, Article 53.

potential for conflicts of interest between those different activities and the interests of their clients. It is therefore necessary to provide for rules to ensure that such conflicts do not adversely affect the interests of their clients (MiFID, recital 29)."

2.2 Disclosure and prevention of financial analysts' conflicts of interest

Disclosure requirements of the MAD

The implementing Commission Directive 2003/125/EC of the MAD concentrates on disclosure requirements for financial analysts. Financial analysts are required to disclose their identity when issuing research (Commission Directive 2003/125/EC, Article 2). Furthermore, analysts have to ensure that, within their published research reports, the facts are distinguishable "*from interpretations, estimates, opinions and other types of non-factual information*" (Commission Directive 2003/125/EC, Article 3(1)).

Moreover, all relevant interests and possible sources for conflicts of interest must be revealed by the relevant persons responsible for the published financial research (analysts or legal persons such as the brokerage firm or investment bank employing them) (Commission Directive 2003/125/EC, Article 5). Further detailed requirements concerning the disclosure of conflicts of interest are specified in Article 6 of Commission Directive 2003/125/EC. Independent analysts, investment banks, brokerage firms and credit institutions (relevant persons) have to disclose major shareholdings and other important financial interests in the covered firm, whether securities underwriting and investment banking services are provided to the covered firm or whether the covered firm pays for the financial research they provide (Commission Directive 2003/125/EC, Article 6(1)).

A conflict of interest for financial analysts, which has been discussed intensely in prior literature, (see, e.g., Mehran and Stulz 2007; Ramnath et al. 2008, for overviews) occurs when investment banks act as underwriters in equity or debt-issuances or as M&A advisors. In both situations, a disclosure statement is required according to Commission Directive 2003/125/EC. In the case of the provision of underwriting services, *"…a statement that the relevant person or any related legal person has been lead manager or co-lead manager over the previous 12 months of any publicly disclosed offer of financial instruments of the issuer"* has to be disclosed in the analyst research report (Commission Directive 2003/125/EC, Article 6(1(d))). An equivalent statement has to be disclosed in the case of investment banking services, such as the provision of M&A advisory (Commission Directive 2003/125/EC, Article 6(1(e))). The disclosure statements required by the MAD for both situations resemble the requirements of the equivalent US regulatory measures (NASD/NYSE 2005; Dubois et al. 2014, p.496).

Additionally, relevant persons have to disclose how conflicts of interest are avoided and prevented by "*effective organizational and administrative arrangements set up within the investment firm or the credit institution*" (Commission Directive 2003/125/EC, Article 6(2)) and whether the remuneration of persons involved in preparing the financial research is linked to investment banking activities of the relevant investment bank (Commission Directive 2003/125/EC, Article 6(3)). Finally, investment firms and banks are required to "*disclose, on a quarterly basis, the proportion of all recommendations that are 'buy', 'hold', 'sell' or equivalent terms, as well as the proportion of issuers corresponding to each of these categories to which the investment firm or the credit institution has supplied material investment banking services over the previous 12 months*" (Commission Directive 2003/125/EC, Article 6(4)).

The conflict of interest disclosures outlined have to be undertaken within the published research reports of financial analysts (Commission Directive 2003/125/EC, Articles 4(2), 5(3), 6(5)).[11] Since financial analysts typically provide different metrics in their research reports such as stock recommendations and target prices, it is important to note that Commission Directive 2003/125/EC, addresses both metrics: *"Recommending or suggesting an investment strategy is either done explicitly (such as 'buy', 'hold' or 'sell' recommendations) or implicitly (by reference to a price target or otherwise)"* (Commission Directive 2003/125/EC, recital 2).

Requirements of the MiFID

The MiFiD and (implementing) Commission Directive 2006/73/EC include organizational requirements (e.g., so-called "*chinese walls"*) and conduct-of-business rules for brokerage firms and banks in order to contain possible conflicts of interest in investment research (e.g., Enriques 2006). Furthermore, also the MiFID requires the disclosure of conflicts of interest, if a successful containment of the conflict is not possible by organizational measures (MiFID, Article 18(2)). Articles 24 and 25 of Commission Directive 2006/73/EC contain specific rules for brokerage firms and investment banks that define how they have to assure that financial analysts do not undertake conflicted personal trading including shares of the covered firms (Commission Directive 2006/73/EC, Article 25(2a)), do not accept incentives from persons with a material interest in the results of the research reports (Commission Directive 2006/73/EC, Article 25(2c)) and do not promise to deliver positive research results to those covered companies (Commission Directive 2006/73/EC, Article 25(2d)).

2.3 Prevention of selective disclosures

According to Article 6(1) of the MAD, firms are required to "*inform the public as soon as possible of inside information which"* relates to the firm. The coherent Article 6(3) of the

[11] However, according to the Articles 4(2), 5(3) and 6(5) of Commission Directive 2003/125/EC, it is possible to disclose con-flicts of interest on a website instead of within the research report, if the reports are quite short compared to the scope of the required disclosure section.

MAD prohibits selective disclosure of inside information to selected individual financial analysts (e.g., Ferrarini 2004). Instead of selective disclosures, firms "*must make complete and effective public disclosure of that information, simultaneously in the case of an intentional disclosure and promptly in the case of a non-intentional disclosure*" (MAD, Article 6(3)). Concerning the prevention of selective disclosures, the MAD follows the regulatory approach of the Reg FD, the relevant US regulatory measure (Ferrarini 2004). Thus the MAD should have the same impact on the interaction between firm management and financial analysts as the Reg FD, which should make it more difficult for analysts with close links to firms to exploit the inside information obtained from selective disclosures (Avgouleas 2005, p. 211).

Furthermore, the organizational requirements contained in Article 13 of the MiFiD (e.g., so-called "*chinese walls*") and in its (implementing) Commission Directive 2006/73/EC should have a constraining impact on a possible "*privileged access*" (Carapeto and Gietzmann 2011, p. 757) for financial analysts to company information (Enriques 2006).

2.4 Implications for the empirical investigation

Implementation process of EU directives

Figure 2.1 follows figure 1 in Christensen et al. (2013b, p. 153) and outlines the identification strategy for regulatory impacts measured by the indicator variables MAD and MiFID, illustrated exemplarily for two different firms listed in two different countries (Firm 1, listed in Germany and Firm 2, listed in the United Kingdom). The Indicator variables take the value of one, when an analyst research report was published after the MAD or MiFID was implemented in a country and otherwise zero.

Figure 2. 1: Illustration of the Identification Strategy for the Impact of Regulatory Changes

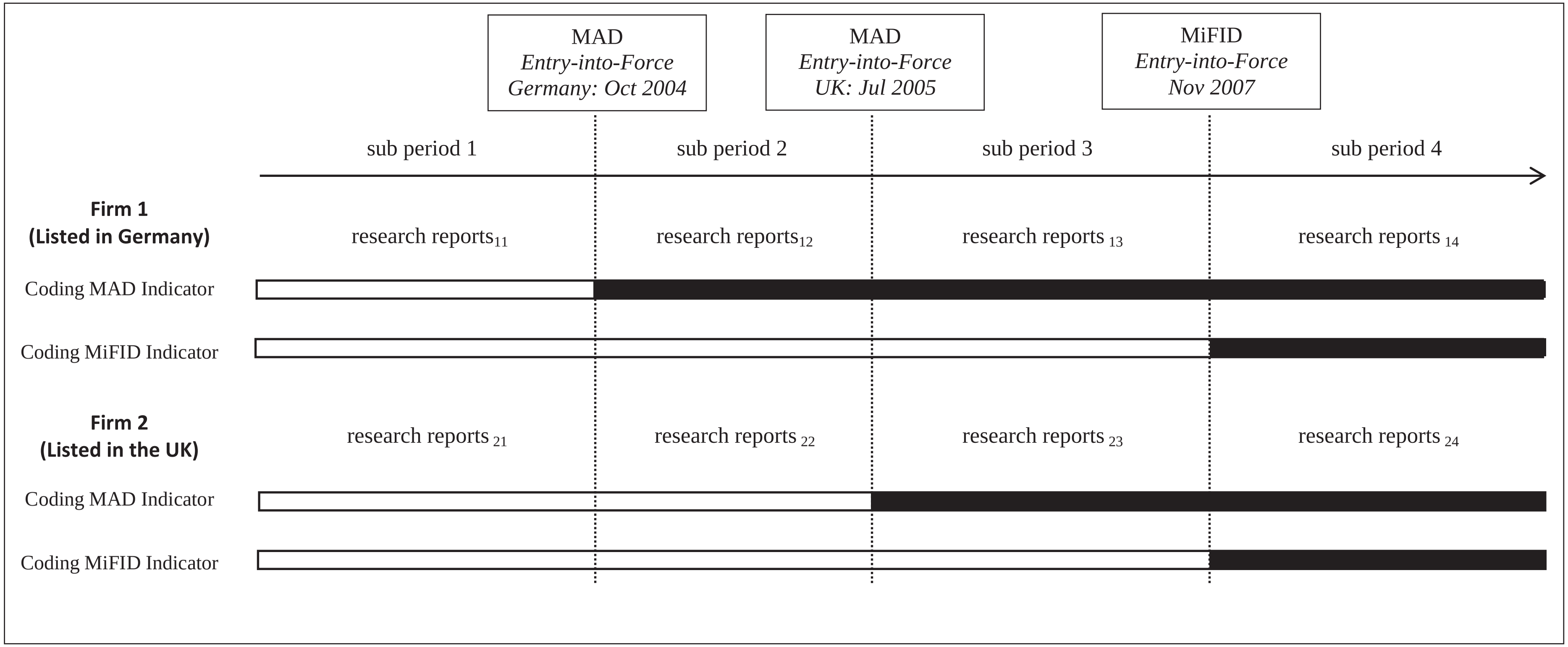


Figure 2.1 follows Figure 1 in Christensen et al. (2013b, p. 153) and outlines the identification strategy for regulatory impact measured by the indicator variables MAD and MiFID, illustrated exemplarily for analyst research reports published in four different sub periods concerning two different firms listed in two different countries (Firm 1, listed in Germany and Firm 2, listed in the United Kingdom). The Indicator variables take the value of one, when a research report was published after the MAD or MiFID was implemented in a country and otherwise zero. An indicator with value one is indicated in black in Figure 2.1.

Figure 2. 2: Implementation timeline of relevant US and European regulatory measures

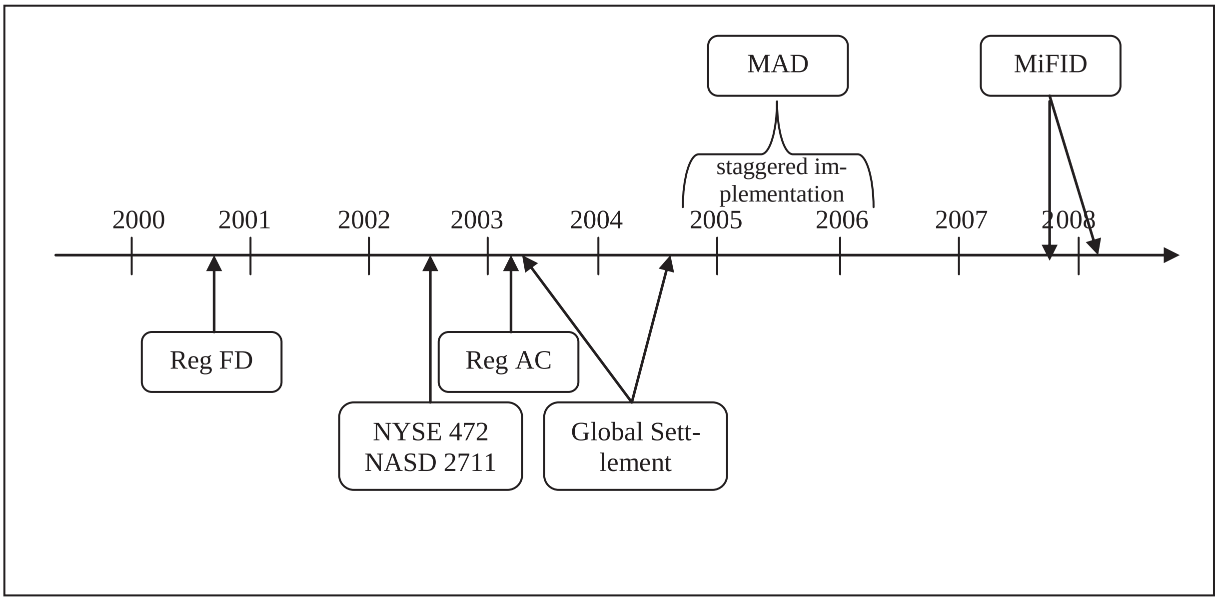


Figure 2.2 shows the implementation timeline of relevant US and European regulatory measures. The implementation dates in the timeline were obtained from Hovakimian and Saenyasiri (2014), Christensen et al. (2016) and from the website of the European Commission.

As can be seen, four periods of time are created, in which analyst research reports are published. While analyst research reports (produced in Germany) about Firm 1 (listed in Germany) are affected by the provisions of the MAD in sub period 2, they are not affected if the analyst research reports (produced in the United Kingdom) are about Firm 2, which is listed in the United Kingdom. In sub period 3, all published analyst research has to comply with the provisions of the MAD but not with the provisions of the MiFID. All analyst research reports published in sub period 4 are affected by the provisions of the MiFID and the MAD. It is significant that the staggered implementation of the MAD becomes discernible. Figure 2.2 outlines the implementation timeline of relevant US and European regulatory measures concerning financial analysts. As can be seen in Figure 2.2[12] the dates of the implementation of MAD range from October 2004 (Germany) to March 2006 (Portugal).[13] According to Christensen et al. (2016, p. 2895), this staggered implementation is brought about by the fact that the EU

[12] And in more detail in Table 3.1.
[13] The range described incorporates the countries included in my samples of the empirical investigations (see chapter 3, 4 and 5 for more details).

directives, in order to become applicable, have to be transposed into the national law of each EU member country, following a rather inflexible transposition process within a window of about two years.

As Christensen et al. (2016, pp. 2895-2896) point out, this rather short transposition window and the rather unyielding processes in the member countries reduce the probability that the timing of implementation is endogenous. Endogenous coming-into-force dates at the EU member state level would imply that local legislators react to local economic shocks or to pressure from local lobby groups Christensen et al. (2016, pp. 2895-2896). However, according to Christensen et al. (2016, p. 2896) who investigate the impact of the MAD on market liquidity, this seems to be very unlikely, since "*countries would have to experience a series of differentially timed local shocks, which in turn would have to prompt national lawmakers to start the country's implementation process for a directive, and this legislative process would have to result in effective dates that coincide with subsequent liquidity changes*".

Moreover, Christensen et al. (2016, p. 2895) point out, that, when investigating the impact of regulatory changes, a staggered implementation helps to mitigate the influence of confounding events on the results. According to Christensen et al. (2016, p. 2895), the results could be influenced by the impact of such concurrent but unrelated confounding events. Moreover, regulatory reforms can be a reaction to an economic crisis or to corporate scandals Christensen et al. (2016, p. 2895). However, in a cross-country setting, such confounding events would have to be associated with the local coming-into-force dates of a regulatory reform in every country included in the sample Christensen et al. (2016, p. 2895).

Like Dubois et al. (2014), my sample includes 13 countries and thus fewer than the study of Christensen et al. (2016), who include 26 countries in their sample. Nevertheless I conclude that a series of local shocks enabling an endogenous coming-into-force, which would coincide with changes in analyst optimism, should also be unlikely in my sample. Furthermore, it also seems to be unlikely that confounding events are associated with local coming-into-force dates of the MAD in every country included in my sample. [14]

As can be seen in Figure 2.2[15], the MiFID was uniformly implemented by the EU member states in November/December 2007, with the exemption of Spain, which implemented the MiFiD shortly afterwards in February 2008. Thus, the outlined advantages of staggered implementation of the MAD, which should help to identify causal effects of the regulatory measure on analyst optimism, do not exist in the case of the MiFID.[16]

Differences in sanction severity between EU member countries

In order to enforce the outlined disclosure requirements of the MAD, EU member states shall assign one single regulator who is competent to assure that the rules of the directives are observed (MAD, Article 11). Furthermore, EU member states have to enable their competent regulator to undertake effective administrative measures and sanctions against persons responsible for infringements of the directive's disclosure requirements (MAD, Article 14(1)).

As a result of this, the severity of sanctions for MAD infringements varies considerably across EU member states, which makes the European setting ideal for measuring how differences in enforcement and sanctions severity influence the behaviour of capital market participants (Dubois et al. 2014; Christensen et al. 2016).

Identification of the competent supervisory authority in the case of cross-border activities

Article 10 of the MAD implies, that in the case of cross-border activities (e.g. if a financial analyst who is located in Member State A prepares a research report about a stock listed in Member State B), then there should exist overlapping responsibilities of the Member States'

[14] See also Dubois et al. (2014, p. 502) who share my judgement.
[15] And in more detail in Table 3.1.
[16] I follow Christensen et al. (2016, p. 2894) and use the dates of the entry-into-force of the last level-2 (implementing) components of the MAD and MiFID as the entry-into-force date in the respective countries. This approach creates at least some variation in the entry-into-force dates between the countries in the sample.

competent authorities. Article 16 (1) MAD requires the competent authorities to ”*cooperate with each other whenever necessary for the purpose of carrying out their duties, making use of their powers whether set out in this Directive or in national law*”. Furthermore, in such cases, competent authorities have to inform and to consult each other “*on the proposed follow-up to their action*” (MAD, Article 16(3)). When Article 10 of the MAD implies that, in the case of cross-border activities, overlapping responsibilities should exist for the Member States’ competent authorities, then the question comes up, which supervisory authority should take action in the case of analyst research reports, which were prepared by an analyst who is located in Member State A about a stock listed in Member State B (Dubois et al. 2014, pp. 497-498). For instance, the BaFin, the German Financial Supervisory Authority, states in its annual report 2006 that it does not monitor analyst research reports which are distributed in Germany but which were prepared in a different EU member country (BaFin 2007, pp. 139-140).[17] However, in addition to the ongoing monitoring of financial analysts and brokerage firms, competent authorities have, as Dubois et al. (2014) point out, a duty to follow up complaints that are filed by investors who feel misled by the stock recommendations, target prices or other components of the research report made by an analyst. Dubois et al. (2014) consider the country of a firm`s primary listing as the relevant jurisdiction when, in the case of cross border activities, administrative authorities from different countries are responsible. Dubois et al. (2014) provide anecdotal evidence and conduct several tests for robustness which support their point of view. I follow the approach of Dubois et al. (2014) and consider the country of a firm`s primary listing as the relevant jurisdiction in the case of the MAD.

[17] “*Financial analyses produced in another EU Member State and distributed in Germany directly from abroad or via a domestic third party (e.g. a domestic branch of a foreign credit institution) are not monitored by BaFin. The authority assumes that the analysis has been produced in accordance with the provisions introduced to implement the Market Abuse Directive in the Member State in question and monitored by the responsible supervisory authority in that state. To enable the law to be applied appropriately but flexibly, BaFin is increasing the level of responsibility held by the companies themselves. This relates in particular to such issues as which affiliated companies are incorporated into the investigation and disclosure of possible conflicts of interest or which other significant financial interests must be disclosed in a financial analysis, as well as the issue of how up to date the data contained in the analysis must be* (BaFin 2007, pp. 139-140).”

In the case of the MiFID overlapping responsibilities also exist for the Member States' competent authorities, since Article 32 of the MiFID allows broker firms to open up branches in other EU member countries. These branches are jointly supervised by competent authorities of the host country in which the branch is situated and the home country of the broker firm (MiFID, Article 32). However, since MiFID was uniformly implemented by all EU member states within November and December 2007, all regulatory authorities had to deal with the provisions of the MiFID and its implementing directive from almost the same coming-into-force date (except in the case of Spain about two months later – in February 2008).[18] Thus, the exact determination of the relevant jurisdiction is not of importance in case of the MiFID.

[18] See Table 3.1 for the per-country Entry-into-force dates of the MAD and MiFID.

3. Analysts' Conflicts of Interest - The Impact of MAD and MiFID on Target Prices[19]

3.1 Introduction

The objective of this paper is to evaluate whether EU-regulatory measures have successfully mitigated the adverse effects of conflicts of interest in sell-side analysts' research.[20] Financial analysts' conflicts of interest are considered to be responsible for positively biased stock recommendations (see, e.g., Mehran and Stulz 2007; Ramnath et al. 2008, for overviews) which, relative to unbiased stock recommendations, can have substantial economic effects such as stock recommendations performing poorly (Michaely and Womack 1999) and the capability to mislead in particular small investors (e.g., Malmendier and Shanthikumar 2007; Mikhail et al. 2007). Evidence in prior research concerning a positive bias in earnings forecasts, caused by conflicts of interest, is less clear (Mehran and Stulz 2007, p. 287).

However, there is growing evidence in recent research that financial analysts use their quantitative measures, stock recommendations, target prices and earnings forecasts in different ways (Malmendier and Shanthikumar 2014; Bilinski et al. 2015). Malmendier and Shanthikumar (2014) provide evidence that analysts do not use stock recommendations and earnings forecasts in the same way and that analysts have, in contrast to their incentives in the case of stock recommendations, only a weak incentive to bias earnings forecasts, since forecasts with a positive bias would damage financial analysts' reputations among institutional investors and would displease the covered firms' management. Bilinski et al. (2015) can show that financial analysts concentrate on biasing target prices instead of stock recommendations

[19] *Acknowledgments:* I am grateful to the following for their valuable comments: Jörg-Markus Hitz, Beatriz Garcia Osma, Olaf Korn, Nico Lehmann, Stefanie Müller-Bloch, Jiří Novák, William P. Rees, Ane Tamayo and participants at the Annual Meeting of the European Accounting Association in Paris, France (May 2013), the Research Seminar in Finance, Accounting and Tax, Göttingen University (June 2013) and the European Accounting Association 30th Doctoral Colloquium in Accounting in Tartu, Estonia (May 2014). A related precursor paper, co-authored with Duc Hung Tran, investigating the impact of European regulatory measures on EPS detail estimates, was presented at the 6th International Workshop on Accounting & Regulation in Siena, Italy (July 2013). I am grateful to Duc Hung Tran for his valuable comments on the utilization of I/B/E/S detail data, which facilitated the conduct of this and other subsequent projects. I am also grateful to Stuart McLeay, Marc Steffen Rapp, Jörg R. Werner and participants at the workshop for their valuable comments.

[20] As Mehran and Stulz (2007, p. 268) point out, a conflict of interest in this context can occur in "*a situation in which a party to a transaction can potentially gain by taking actions that adversely affect its counterparty*".

or earnings forecasts. Due to the higher granularity of target prices in comparison to the typical five-tier or three-tier schemes of stock recommendation rating systems, target prices are a more suitable metric for conflicted analysts to convey a biased opinion, as Bilinski et al. (2015, p. 5) point out.[21]

This paper focuses on target prices, which are, as well as earnings forecasts and stock recommendations, an important quantitative measure in analysts' investment research (e.g., Brav and Lehavy 2003; Demirakos et al. 2010). Although there is evidence that target prices convey new information in addition to that contained in stock recommendations and earnings forecasts (Asquith et al. 2005; Arand et al. 2015), they have been neglected by prior research (Bradshaw et al. 2014, p. 4). Moreover, the recent studies by Bradshaw et al. (2014) and Arand and Kerl (2015) provide evidence that target prices can also be biased by those conflicts of interest addressed by the regulatory measures in the US and Europe.

In the European Union, two directives, the MAD (Market Abuse Directive, introduced in 2003) and the MiFID (Markets in Financial Instruments Directive, introduced in 2004), have, amongst other objectives, the mitigation of conflicts of interest in the field of the financial analysts' investment research (MiFID, recital 29; MAD, Article 6(5)). Both directives are accompanied by implementing directives (Commission Directive 2003/125/EC and Commission Directive 2006/73/EC), which contain detailed regulations concerning the presentation of financial research results and the prevention and disclosure of possible conflicts of interest. An important element of the disclosure requirements in Commission Directive 2003/125/EC is the compulsory disclosure of several types of potential conflicts of interest within the analyst research reports (Commission Directive 2003/125/EC, Articles 4(2), 5(3), 6(5)).[22] One important category of conflict of interest, which has been intensely examined in prior research

[21] Moreover, Kadan et al. (2009) provide evidence of a change from five-tier to three-tier stock recommendation among US broker firms caused by regulatory measures, which reduced the granularity of stock recommendations even more.

[22] However, according to Articles 4(2), 5(3) and 6(5) of Commission Directive 2003/125/EC, it is possible to disclose conflicts of interest on a website instead of within the research report, if the reports are quite short compared to the scope of the required disclosure section.

(e.g., Lin and McNichols 1998; Michaely and Womack 1999; Ljungqvist et al. 2007; Kolasinski and Kothari 2008), is addressed by Article 6 (1(d)) and Article 6 (1(e)) of Commission Directive 2003/125/EC: if the bank or brokerage firm, which employs the relevant financial analyst, provided securities, underwriting or other investment banking services to the covered firm, then this conflict of interest has to be disclosed within the research report. The MiFiD and its implementing Commission Directive 2006/73/EC are geared up to containing possible conflicts of interest in analyst research by introducing and strengthening organizational requirements (e.g., so-called "*chinese walls*") and conduct-of-business rules for brokerage firms and banks (Enriques 2006). All directives have to be transposed into national law by EU-Member countries in order to become applicable.[23]

Although the European regulatory measures explicitly address target prices[24], they are more geared towards stock recommendations (Dubois et al. 2014, p. 495). Consequently, Article 6(3) of Commission Directive 2003/125/EC requires banks and brokerage firms employing analysts to disclose, separately and with a quarterly frequency, tables which include the distributions of all their unaffected and their conflicted buy/hold/sell recommendations. Thus, investors can detect whether analysts are on average more likely to issue buy recommendations for covered firms to which their employing bank or brokerage firm has close links through the provision of underwriting or other investment banking services. Thus, these tables can be considered a key element of the disclosure regulation, which should have a disciplining impact on financial analysts.[25] However, analysts and their employers are not required to disclose anything comparable in the case of target prices (Staikouras 2008, p. 370). Thus, in the post-regulation period, this disclosure requirement makes target prices a less obvious measure for sending an overly optimistic opinion.

[23] See MAD, Article 18; Commission Directive 2003/125/EC, Article 10; MiFID, Article 70; Commission Directive 2006/73/EC, Article 53.
[24] See Commission Directive 2003/125/EC, recital 2.
[25] They can roughly be compared to the "*name and shame*"- approach, applied in accounting enforcement (Hitz et al. 2012, p. 254).

The impact of regulatory changes which are geared towards mitigating analysts' conflicts of interest in the U.S. have already been examined in several studies[26]. To my knowledge, aside from Prokop and Kammann (2017), who investigate earnings forecasts, and Höfer and Oehler (2014), who provide some evidence based on mean comparison tests, Dubois and Dumontier (2008) and Dubois et al. (2014) are the only studies which concentrate on examining the effects of the European regulatory measures on financial analysts' stock recommendations in a cross-country setting.

Following Dubois and Dumontier (2008) and Dubois et al. (2014), this study exploits the unique European regulatory setting in order to investigate the impact of regulatory measures on target prices and stock recommendations. A remarkable feature of the MAD is that substantial differences exist across the EU-Member countries concerning the time of implementation, the severity of sanctions and the rigidity of enforcement (Christensen et al. 2016). Thus, the European Union represents an ideal setting for the investigation of the impact of regulatory changes, since the staggered implementation of the MAD across EU-Member countries creates a unique setting for empirical research and facilitates the identification of regulatory effects (Christensen et al. 2016).

In addition to exploiting the staggered implementation of the MAD, which should facilitate an accurate identification, a Difference-in-Difference (DiD) regression design is applied in order to identify the impact of the introduction of the MAD and MiFID on the optimism and informativeness of analysts' target prices for a sample of firms listed in 13 EU member countries. As in Dubois et al. (2014), I will concentrate on one important conflict of interest, which is addressed by Article 6 (1(d)) and Article 6 (1(e)) of Commission Directive 2003/125/EC, the impact of securities, underwriting and M&A advisory activities on affiliated analysts, who are employed by banks or brokers providing these services to the firms that are covered. As a

[26] E.g., Barber et al. (2006); Barniv et al. (2009); Chen and Chen (2009); Kadan et al. (2009); Hovakimian and Saenyasiri (2010); Guan et al. (2012); Hovakimian and Saenyasiri (2014).

first step, I replicated the baseline model of Dubois et al. (2014) in order to validate my affiliation identification approach. As in Dubois et al. (2014), my results show that the MAD had a mitigating impact on over-optimism in affiliated analysts' stock recommendations. Concerning optimism in target prices, I find a highly significant positive impact of the regulatory measures MAD and MiFID on the target price optimism of affiliated analysts. Thus, my results provide evidence that analysts use their quantitative metrics in different ways. Moreover, these results imply that target prices are an eligible measure for sending overly optimistic signals to investors in the post-regulation period. Moreover, I cannot find a reduced informativeness of affiliated target price revisions in the post-regulation period, which implies that market participants cannot look through the incentives of affiliated analysts thoroughly, since they do not discount target price revisions properly. In conclusion, I interpret my findings as an indication of an "*avoidance strategy*" (Leuz and Wysocki 2016, p. 536) applied by financial analysts, who have an economic incentive to bias their research outputs even in the post-regulation period. Since the disclosure requirements of the MAD are geared more explicitly towards stock recommendations, it is less risky for analysts to bias their target prices instead of stock recommendations after the introduction of the MAD. Moreover, this practice is not mitigated by the organizational requirements and conduct-of-business rules, which were introduced by the MiFID.

This paper augments prior literature in several dimensions. First, Dubois et al. (2014) concentrate their investigation on stock recommendations, which, based on the results of Malmendier and Shanthikumar (2014), are considered to be the more biased measure in comparison to earnings forecasts. A recent and growing stream of literature focuses on analysts' target prices, which contain, compared to discrete stock recommendations, more forthright valuation implications (Bradshaw et al. 2013). Thus, this study augments prior literature by examining the impact of the regulatory measures on target prices and reacts, like the studies of Bilinski et al. (2013), Bradshaw et al. (2014) and Bilinski et al. (2015) to the call for more research by Ramnath et al. (2008, p. 68), who state, that "*further research is required to describe the behavior of the forecasts that have higher price impacts, such as long-term growth forecasts and target prices*".

Second, while Dubois et al. (2014) and Hovakimian and Saenyasiri (2014) investigate the impact of the MAD on financial analysts' conflicts of interest, there is, to my knowledge, besides Prokop and Kammann (2017), who investigate earnings forecasts, and the study of Höfer and Oehler (2014), who apply mean comparison tests, no study which applies multivariate analysis in order to investigate the impact of the MiFID on target prices and recommendations. Thus this study contributes to the existing literature on the regulation of financial analysts by examining the effects of the MiFID on financial analysts' target prices and recommendations.

Third, by exploiting the "*time-series variation*" (Leuz and Wysocki 2016, p. 571) of the introduction process and the "*cross-sectional variation*" (Leuz and Wysocki 2016, p. 571) in the sanction severity of the MAD this study adds to the growing stream of literature, which investigates the impact of regulatory changes on the basis of the unique European regulatory environment (e.g., Christensen et al. 2013b; Dubois et al. 2014; Christensen et al. 2016).

The remainder of this paper is organized as follows. In section 3.2, possible sources for conflicts of interest are presented together with the relevant related literature. Section 3.3 develops empirical predictions. Section 3.4 outlines the methodology. Section 3.5 presents the sample construction and the empirical findings. The final section 3.6 concludes.

3.2 Background

3.2.1 The influence of analysts' conflicts of interest on analysts' behaviour

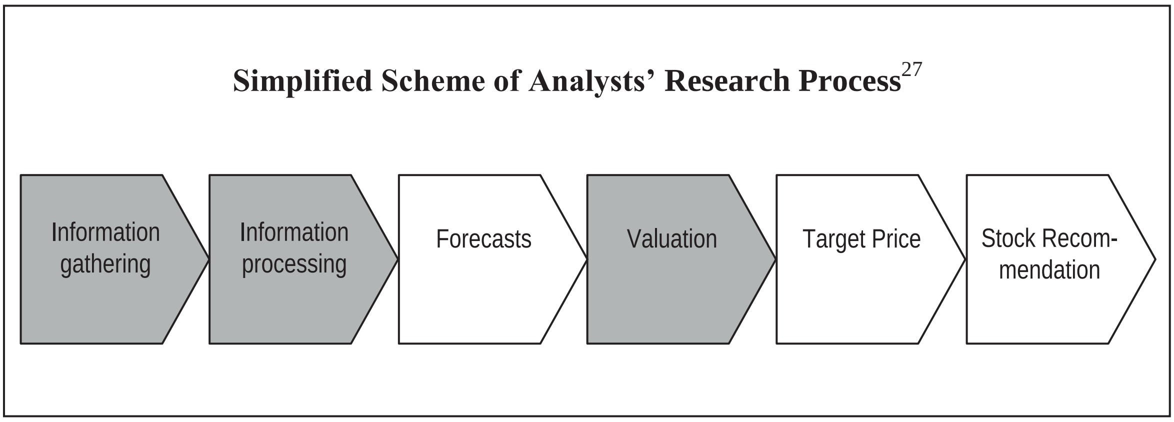
Figure 3.1 provides a simplified scheme of a financial analysts' research process. Analysts gather information about firms from various public sources, process information and, besides textual analysis in their written reports, typically provide three different quantitative measures: earnings forecasts, target prices and stock recommendations (Brav and Lehavy 2003, p. 1933; Asquith et al. 2005, p. 255; Bradshaw 2009, p. 1076; Demirakos et al. 2010, p. 37; Bradshaw et al. 2013, p. 931). Whereas information gathering and processing can be seen as “*black boxes*” (Bradshaw 2009, p. 1076), the quantitative measures can be obtained from analyst research reports (e.g., Asquith et al. 2005). However, including target prices in research reports was not that common up to the mid-1990s, as Gleason et al. (2013, p. 80) point out:

“By the mid-1990s, a growing number of sell-side equity analysts had begun to disclose price targets in their published stock research reports. Price targets are presumably intended to convey analysts’ opinions about what a stock is truly worth and thus form the basis for their less granular buy–sell recommendations.”

Moreover, it is not obvious, how target prices are used by financial analysts:

“Price targets can be either a way for analysts to ameliorate the effects of overly optimistic reports or a part of the sales hype used to peddle stocks Asquith et al. (2005, p. 276)*.”*

Figure 3. 1: Analyst Research Process



[27] The scheme follows Bradshaw (2009), Figure 1, p.1076.

Evidence of an optimistic bias in financial analysts' earnings forecasts and in stock recommendations has been found in numerous empirical studies. A survey of relevant studies for the US capital market is provided by Mehran and Stulz (2007) and Ramnath et al. (2008). Capstaff et al. (2001) provide evidence of overly optimistic earnings forecasts in nine different European countries within the period 1987-1994. Wallmeier (2005) shows that financial analysts delivered earnings forecasts too optimistic for DAX-100 firms within the years 1991-2000 and McKnight et al. (2010) document that underwriter financial analysts' earnings forecasts and stock recommendations for European firms are overly optimistic.

Over-optimism can be caused by conflicts of interest to which financial analysts are exposed. Hovakimian and Saenyasiri (2010), Bradshaw (2011) and Karamanou (2011) categorize different potential sources of conflict.[28]

First, conflicts of interest can be triggered by the investment banking business, when sell-side analysts that are working for investment banks are pressurized into providing favorable forecasts or recommendations in order to please current or potential future customers of their employer's investment banking department (Karamanou 2011, p. 2). This source of conflict might be prevalent since sell-side research within investment banks is to be considered as a cost-centre (Bradshaw 2011, p. 26). For instance, Michaely and Womack (1999) and Kolasinski and Kothari (2008) provide empirical evidence on this link.

Second, analysts could try to maintain preferred access to managers of the covered firms by pleasing them with overly optimistic forecasts (Bradshaw 2011, p. 26). E.g., Lim (2001) and Richardson et al. (2004) provide evidence on this source of conflict.

Third, sell-side analysts could be pressurized into biasing their reports because optimistic forecasts and recommendations generate a higher trading volume and thus higher commissions for their employer than pessimistic ones (Karamanou 2011, p. 2), since "*it is easier to*

[28] Bradshaw (2011, pp. 26-28) ranks the sources of conflict of interest for financial analysts according to their relative importance in the literature (descending order). I follow the ranking of Bradshaw (2011) in my portrayal of analysts' conflicts of interest.

convince an investor to buy a stock that they do not own rather than convincing them to sell a stock they must already own" (Bradshaw 2011, p.27). E.g., Jackson (2005) and Cowen et al. (2006) provide evidence on this source of conflict.

Fourth, according to Bradshaw (2011, p. 27), close relations with customers could be another source of conflict, which can be the case, when there are close links between institutional investors and the investment bank that employs the financial analysts or when analysts are hired and thus paid for covering a company.

Fifth, the analysts themselves could be a source of conflict, since there is evidence that analysts are reluctant to publish negative forecasts or sell recommendations for companies to whom they developed a strong affinity (Bradshaw 2011, pp. 27-28).

Remarkably, the overall evidence of empirical studies on financial analysts' conflicts of interest shows that positively biased earnings forecasts seem to be less common than too optimistic stock recommendations (Mehran and Stulz 2007, p. 287).

Wallmeier (2005, p. 132) outlines several possible explanations why the conflicts of interest might have a weaker effect on earnings forecasts:

One reason could be, according to Wallmeier (2005, p. 132), that overly optimistic forecasts are easier to detect at the end of the forecast period than biased recommendations. Thus, too high earnings forecasts could have a negative effect on financial analysts' reputations and compensation, since their employers' internal ranking systems are based on forecast accuracy in most cases (Wallmeier 2005, p. 132). Furthermore, analysts that are interested in good relations with a firm's management pay attention to maintaining their earnings forecasts on a moderate level shortly before the earnings announcement date, since the management has an incentive "*to meet or beat*" financial analysts' earnings forecasts (e.g., Degeorge et al. 1999; Bartov et al. 2002, p. 202; Wallmeier 2005). This interaction between analysts and firm management is known as "*forecast-guidance*" in the literature (e.g., Matsumoto 2002). A typical feature of "*forecast-guidance*" is, that "*analysts first issue optimistic earnings forecasts and* *then 'walk down' their estimates to a level that firms can beat at the official earnings announcement*" (Richardson et al. 2004, p.885).

Malmendier and Shanthikumar (2014) provide evidence that analysts "*speak in two tongues*" (Malmendier and Shanthikumar 2014, p. 1), which means, that they use their stock recommendations and earnings forecasts in two different ways.

Analysts have, according to Malmendier and Shanthikumar (2014, p. 1289), an incentive to strategically bias their recommendations in order to induce small investors to buy stocks, while large investors correct for the positive bias in recommendations. However, analysts have a much weaker incentive to bias earnings forecasts because positively biased forecasts would damage analysts' reputations among institutional investors and would displease firm management, since biased forecasts could hamper "*forecast-guidance*" (Malmendier and Shanthikumar 2014, p. 1289).

Interestingly, the research literature has focused on stock recommendations and earnings forecasts and neglected the third relevant quantitative measure, target prices (Bradshaw et al. 2014, p. 4). Nevertheless, there is evidence that target prices convey incremental information in addition to the information contained in stock recommendations (e.g., Asquith et al. 2005). Moreover, the recent studies by Bradshaw et al. (2014) and Arand and Kerl (2015) provide evidence that target prices can be biased by conflicts of interest, too.

Due to their "*high granularity compared to stock recommendations, which allows more degrees of freedom for the analyst to bias the forecast*" (Bilinski et al. 2015, p. 5), target prices could be a much more advantageous measure for conflicted financial analysts to convey their biased opinion, as Bilinski et al. (2015, p. 5) point out. Consequently, Bilinski et al. (2015) provide evidence that analysts prefer to bias target prices compared to stock recommendations and earnings forecasts.

Thus, there is growing evidence, that financial analysts use their quantitative measures stock recommendations, target prices and earnings forecasts in different ways. As outlined above, earnings forecasts are less suitable to channel a biased opinion. Stock recommendations and target prices seem to be much more advantageous for analysts in conflict (Bilinski et al. 2015). Moreover, when comparing target prices with stock recommendations, the latter appear to be more strictly and more critically monitored by regulators and investors, making target prices an even more inconspicuous measure for channeling a biased opinion (Bilinski et al. 2015, p.5).

3.2.2 Related literature

The economic consequences of regulatory changes, which are geared towards mitigating analysts' conflicts of interest and the prevention of selective disclosures in the U.S. and the European Union, have been examined in several studies. Figure 2.2 outlines the implementation timeline of relevant US and European regulatory measures concerning financial analysts. While the US-regulatory measures NYSE Rule 472, NASD Rule 2711, Regulation Analysts Certification (Reg AC) and the Global Settlement concentrate on rules for the disclosure and prevention of conflicts of interest in investment research, Regulation Fair Disclosure (Reg FD) concerns the prevention of selective disclosures (e.g., Contoudis 2003; Hovakimian and Saenyasiri 2010; Koch et al. 2013; Hovakimian and Saenyasiri 2014). In the European Union, conflicts of interest in analysts' research are addressed by two directives, the MAD (Market Abuse Directive) and the MiFID (Markets in Financial Instruments Directive) (e.g., Ferrarini 2004; Enriques 2006).

Barber et al. (2006) and Kadan et al. (2009) investigate the impact of U.S. regulatory measures (NASD Rule 2711, NYSE Rule 472 and Global Analyst Research Settlement) on stock recommendations and find a decline in the proportion of buy recommendations. Moreover, Kadan et al. (2009) provide evidence of a change to a more coarsely granular three-tier rating scheme for stock recommendations among leading investment banks and find evidence of increased informativeness of optimistic recommendations, but an overall decrease in recommendation informativeness after the new NYSE Rule 472, NASD RULE 2711 and the Global Settlement came into force. The increased informativenness might be caused by a reduced prevalence of optimistic buy recommendations, the overall reduced informativeness by a change of the rating schemes from a five-tier to a three-tier scale (Kadan et al. 2009).

Chen and Chen (2009) and Barniv et al. (2009) investigate the association between financial analysts' stock recommendations and their earnings forecast-based valuation and find a strengthening positive impact of NASD Rule 2711 and Reg FD on this link. Hovakimian and Saenyasiri (2010) investigate the effect of Regulation Fair Disclosure (Reg FD) and the Global Research Analyst Settlement on analysts' earnings forecasts and find a significantly reduced forecast bias in both cases. Hovakimian and Saenyasiri (2014) investigate potential spillover effects of the Global Analyst Research Settlement on financial analysts' investment research in 40 countries around the world. Hovakimian and Saenyasiri (2014) find a significantly reduced forecast bias especially in countries with rather low investor protection. Furthermore, they investigate whether the introduction of the MAD reduced the bias in earnings forecasts in EU-member countries. However, the MAD does not have a significant impact on the forecast bias in the study of Hovakimian and Saenyasiri (2014).

Cornett et al. (2007) find a change in capital market participants' reaction to stock recommendation changes of affiliated versus unaffiliated analysts after Reg FD. According to Cornett et al. (2007), before the introduction of Reg FD, affiliated analysts' recommendation downgrades induced significantly stronger stock price reactions than downgrades issued by unaffiliated analysts. Cornett et al. (2007) presume this was caused by the belief of investors that affiliated analysts have privileged access to firm management and thus should receive selectively disclosed information. Cornett et al. (2007) find that this difference in investors' reactions to recommendation changes disappears, after Reg FD came into force. Moreover, Cornett et al. (2007) find a significant overall decrease in the reactions of stock prices to recommendation changes of both affiliated and unaffiliated analysts after the introduction of Reg FD, which could be the result of a behavioural change in the analysts or could be caused by firms, which want to assure no violation of Reg FD rules and thus are less forthcoming with information.

Shahzad and Mertens (2017) study the impact of the MAD on financial analysts' forecast accuracy, forecast dispersion and analyst coverage in the German capital market. Shahzad and Mertens (2017) find an increase in the forecast accuracy, decreased forecast dispersion and decreased analyst coverage after the implementation of the MAD. However, since they concentrate on one EU-member country, they cannot examine the effect of differences in sanction severity and enforcement across countries on the regulatory outcome.

To my knowledge, Prokop and Kammann (2017), Dubois et al. (2014), Höfer and Oehler (2014), who provide some evidence based on mean comparison tests, and Dubois and Dumontier (2008) are the only studies which concentrate on examining the effects of the European regulatory measures on financial analysts' in a cross-country setting. Prokop and Kammann (2017) investigate the impact of the MiFID on earnings forecasts and find a reducing impact of the MiFID on affiliated analysts' conflicts of interest. The study by Dubois et al. (2014) investigates the impact of the MAD on stock recommendations' optimism in 13 EU-member countries and provide evidence that the introduction of the MAD has reduced the effects of conflicts of interest, with a stronger mitigating impact in countries with a stricter enforcement regime. However, Dubois et al. (2014) do not analyse the effects of the MAD on financial analysts' earnings forecasts or target prices. Furthermore, they ignore the MiFID, the second relevant directive. Dubois and Dumontier (2008) provide evidence for the impact of the MAD on informativeness of stock recommendations. Dubois and Dumontier (2008) find an increased informativeness of stock recommendation upgrades, downgrades and positive initiations after the MAD came into force.

3.3 Empirical predictions

Analyst over-optimism

When analysing MAD and MiFID, a relevant research question arises whether the regulative measures met their objectives in the field of conflicts of interest in financial analysts' research. The objective of the two directives is to restrict the adverse effects of conflicts of interest by requiring the disclosure of all information concerning possible conflicts of interest (for example, when a financial institution, employing analysts, acted as an underwriter in equity- or debt-issuances or as M&A advisor) and, in the case of investment firms, the obligation to take adequate measures in order to prevent conflicts of interest (MiFID, recital 29; MAD, Article 6(5)). Sufficient disclosure (in the case of the MAD) and the implementation of effective organizational requirements and conduct-of-business rules (in the case of the MiFID) should successfully mitigate analysts' conflicts of interest. If this is the case, the regulatory reforms should result in a reduced positive bias in research outputs by affiliated analysts (i.e. analysts working for brokers, who act or acted as underwriters or M&A advisors to the firm under analysis) (Dubois et al. 2014).

Dubois et al. (2014) find a significant reducing impact of the MAD on over-optimism in affiliated analysts' stock recommendations. Kadan et al. (2009) find comparable results in their investigations of equivalent US regulatory reforms on stock recommendations. This focus on stock recommendations seems comprehensible since "*stock recommendations were the focal point of many complaints of conflicts of interest and because conflicted equity research primarily takes place via biased recommendations rather than through biased earnings' forecasts*" (Dubois et al. 2014, p. 499).[29]

Kadan et al. (2009) provide evidence that numerous banks and brokerage houses changed their stock recommendation rating system from a five-tier scheme to a more coarsely granular three-tier rating scheme after the introduction of analyst regulatory measures in the US.

[29] See also Kadan et al. (2009, p. 4194) who point out that stock recommendations were also the focus of the demands for regulatory reforms in the USA.

Kadan et al. (2009) argue that this change was provoked by the compulsory disclosure of the distribution of unaffected and conflicted buy/hold/sell recommendations, which was also introduced within the scope of the analyst regulations in the US. Thus, the granularity of stock recommendations was further reduced by regulatory measures and consequently the eligibility of recommendations to convey optimism might have been lowered even more (Kadan et al. 2009).[30] Earnings forecasts, the third common measure provided by analysts, are less suitable for sending overly optimistic signals to investors because overly optimistic earnings forecasts could damage the reputation of analysts among institutional investors and would displease firm management, since positively biased earnings forecasts could hamper "*forecast-guidance*" (Malmendier and Shanthikumar 2014, p. 1289).

However, neither Dubois et al. (2014) nor Kadan et al. (2009) consider target prices in their investigations. As pointed out, the studies by Arand and Kerl (2015) and Bradshaw et al. (2014) provide the first evidence that target prices can also be biased by conflicts of interest. Moreover, due to their "*high granularity*" Bilinski et al. (2015, p. 5) and because stock recommendations are more strictly and more critically monitored by regulators and investors, target prices could be a much more suitable measure for conflicted financial analysts to convey a biased opinion (Bilinski et al. 2015, p. 5).

In addition to the granularity of target prices, which facilitates the conveyance of over-optimism "*in more subtle ways*" (Kadan et al. 2009, p. 4195) by simply announcing a target price that is moderately too high, the MAD requires, as pointed out, banks and broker firms, employing analysts, to disclose separately and with a quarterly frequency the distributions of all their unaffected and their conflicted buy/hold/sell recommendations.[31] This disclosure re-

[30] Moreover, it is important to note that Kadan et al. (2009) investigate changes of rating systems among investment banks in the US. A substantical fraction of investment banks operating in the US have subsidiaries also in the EU. My sample of stock recommendations and target prices includes a substantial number of investment banks operating in the US and the EU, thus there should have been an impact of the rating system changes also on the European market.

[31] Although Kadan et al. (2009) refer to earnings forecasts, this argument should also be applicable in the case of target prices.

quirement should make target prices a less visible and thus, an even more eligible measure for sending overly optimistic signals to investors in the post-regulation period.

The incentive for affiliated analysts to bias target prices could also persist after the introduction of the MiFID. Although the MiFID might have established information barriers by introducing and strengthening organizational requirements ("*chinese walls*"), it is unlikely that all interactions between investment banking departments (securities underwriting and M&A advisory) and equity research within a financial institution have been shattered after MiFID became active.[32]

Furthermore, equity research analysts should, even when not involved in deal-related research, be aware of underwriting and M&A advisory activities which have recently taken place. Although direct monetary inducements for research analysts from the securities and M&A-business are forbidden according to the MiFID, bonus payments based on the total result of a company are still allowed in some cases.[33] Thus, analysts could, even when they are not influenced by bonus payments related to their company's results, still be unwilling to cause annoyance to customers of their employer's investment banking department after the introduction of the MiFID.[34] They could achieve this by sending overly optimistic signals to investors with the help of biased target prices.

Therefore, I predict that affiliated analysts have an incentive to maintain, or even to increase, their bias on target prices in the post-MAD and post-MiFID period (Prediction I).

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[32] For instance, financial analysts are still allowed to take part in road shows and sales pitches of their employing investment bank – thus, the provision of research in the context of IPOs or Seasoned Equity Offerings (SEOs) is still allowed in the post-MAD and post-MiFID period (Staikouras 2008, p. 370).

[33] At least, in the case of banks and brokerage firms which are regulated by the German financial authority (Roth 2014, p. 651, 657). However, individual IPOs, SEOs or M&A transactions, which could be influenced by an analyst, should not have a significant impact on the total result of a company (Roth 2014, p. 651, 657). Thus banks and brokerage firms must be of an appropriate size in order to adopt total result-related bonus payments for analysts (Roth 2014, p. 651, 657).

[34] Contoudis (2003, p. 133-134) distinguishes between "*political pressure*" to issue overly optimistic opinions about customers of analysts' employer's investment banking department and economic conflicts for financial analysts. According to Contoudis (2003, pp. 133-134), the latter can also result in over-optimism, when the compensation for analysts depends on the success of their company's investment banking department.

Informativeness of analysts' target prices

Prior studies investigating the informativeness of analysts' reports found differences in the prices reactions to stock recommendations issued by affiliated and unaffiliated analysts. Michaely and Womack (1999) provide evidence that "*buy*" recommendations, which were issued by affiliated analysts, cause smaller positive stock market reactions than those issued by unaffiliated analysts, but the difference is significant only at a marginal level. Lin and McNichols (1998) find significantly more negative market reactions to "*hold*" recommendations issued by affiliated analysts compared to those issued by unaffiliated analysts. In addition to that, as Kadan et al. (2009, p. 4213) and Mehran and Stulz (2007, p. 279) sum up, there is evidence that investors are able to account for the incentives of affiliated analysts and to discount[35] such stock recommendations.[36]

Taken altogether, most prior research concentrated on stock recommendations when investigating whether affiliated and unaffiliated analysts' research cause different stock market reactions and when investigating the impact of regulatory reforms on the informativeness of analyst research.[37] Target prices, being more granular and unaffected by rating system changes[38], should be an appropriate analyst item for measuring whether the market participants understand and thus whether they account for the incentives of affiliated analysts. When investors are able to account for the incentive of affiliated analysts with regard to target prices, their reactions to their target price revisions should not be stronger after the introduction of the regulatory measures.

[35] "*If an analyst's recommendations are biased despite labor market incentives, the bias will not necessarily have an impact on security prices if the capital markets discount them to adjust for the bias. Similarly, the bias might not affect the investment decisions of investors who take it into account*" (Mehran and Stulz 2007, p. 279).
[36] Moreover, as already pointed out in the section relevant literature, prior research finds a significant impact of relevant regulatory reforms on informativeness of affiliated analysts' stock recommendations to some extent (Kadan et al. 2009; Loh 2009; Dubois and Dumontier 2008; Cornett et al. 2007).
[37] E.g., with the exception of Dechow et al. (2000), who investigate long-term earnings growth forecasts.
[38] Kadan et al. (2009) find that changes in the rating system had a negative impact on overall informativeness of stock recommendations.

Consequently, I predict the informativeness of target price revisions by affiliated analysts in the post-MAD and the post-MiFID period to be unchanged or even negative (Prediction II).

3.4 Research design

3.4.1 Identification strategy and econometric model

$$OPT\_METRIC_{i,j,t} = \beta_0 + \beta_1 RegIndicator + \beta_2 Affiliation + \beta_3 RegIndicator \times Affiliation$$
$$+ \sum \beta_j Controls_j + \sum \beta_j Fixed\ Effects_j + \varepsilon \qquad (1)$$

$$MAR_{i,j,t} = \beta_0 + \beta_1 RegIndicator + \beta_2 TP\_REV + \beta_3 Affiliation + \beta_4 RegIndicator$$
$$\times TP\_REV + \beta_5 RegIndicator \times Affiliation + \beta_6 TP\_REV \times Affiliation$$
$$+ \beta_7 RegIndicator \times TP\_REV \times Affiliation + \sum \beta_j Controls_j$$
$$+ \sum \beta_j Fixed\ Effects_j + \varepsilon \qquad (2)$$

I follow Dubois et al. (2014) and apply a Difference-in-Difference (DiD) regression design to measure the impact of the introduction of the MAD and MiFID on analyst optimism of affiliated broker firms.[39] When investigating a regulatory change, the DiD-design controls the common trends, which are time-variant and affect both the treated and untreated group but which are not caused by the regulatory reform itself (the introduction of the MAD or MiFID in my setting) (Roberts and Whited 2013, pp. 520-531; Guan et al. 2012, p. 448).

In addition to the DiD-design, the outlined staggered implementation of the MAD strengthens the empirical approach and should further facilitate an accurate identification of the impact of the MAD, since it diminishes the potential impact of confounding regulatory reforms and other confounding market-wide events as well as considerations respective the

[39] See also Roberts and Whited (2013, pp. 520-531) for more details on the DID-design.

endogeneity of the timing of the implementation of regulatory reforms (Dubois et al. 2014, p. 502).

Moreover, like Dubois et al. (2014), I concentrate on one important conflict of interest, which was examined extensively in prior research and which is addressed by Article 6 (1(d)) and Article 6 (1(e)) of Commission Directive 2003/125/EC: the impact of securities underwriting and M&A advisory activities on affiliated analysts (analysts employed by the same broker house). As outlined, Commission Directive 2003/125/EC requires broker firms to disclose such conflicts of interest in their research reports.

Thus, *Affiliation* is defined as the treatment assignment indicator variable in my DiD-design, which takes the value of one when a stock recommendation or target price was issued[40] by an affiliated broker firm – a broker firm which acted as an underwriter in equity (IPOs, SEOs), debt-issuances or as M&A advisor for the covered firm within the last 365 days before a recommendation or target price was issued and otherwise zero. *RegIndicator* is the post-treatment indicator variable, taking the value of one when a stock recommendation or target price is released after the MAD or the MiFID has been implemented in a country and otherwise zero. Accordingly, the indicator variable *RegIndicator×Affiliation* takes the value of one, when a stock recommendation or target price, which is part of the treatment group, is issued in the post-treatment period and otherwise zero. Stock recommendations or target prices, which were issued by analysts employed by unaffiliated broker firms, are used as the control group in my DiD-design.

The indicator variables of my DiD-design are added to a comprehensive set of control variables at the level of both broker and firm. I adopt the fixed effects structure of Dubois et al. (2014) and further refine it by adding industry-fixed. Hence, my fixed effects structure includes broker-, industry-, year- and country-fixed effects. Taken altogether, this econometric

[40] The date when a target price or recommendation is activated (activation date) in the I/B/E/S data base is used.

approach should facilitate an accurate identification of the regulatory impacts and should enable causal inference to be deduced (Lehmann 2016, pp. 17-18).[41]

In order to test my *Prediction I*, model 1 is specified. The dependent variable (*OPT_METRIC*) in model 1 is either stock recommendation optimism (*RECO*) or target price optimism (*TPO*). In order to be in line with *Prediction I*, the estimated coefficient β_3 should have a positive sign.

Prediction II, is tested on the basis of the event-study approach of model 2, which includes market adjusted returns (*MAR*) as the dependent variable and includes, as a further explanatory variable, target price revisions ($TP\_REV_{i,j,t}$). Revisions of the target price are defined as the percentage change in the target price of a broker i on a firm j when compared with the previous target price by the same broker on the same firm. Definition is analogue to Arand et al. (2015). $TP\_REV_{i,j,t}$ is winsorized at the 1% and 99% percentiles. Thus, the interaction-term *RegIndicator* × *TP_REV* × *Affiliation* measures the variation in the impact of revisions of the target prices, issued by broker firms which are part of the treatment group, which was caused by the treatment. In order to be in line with *Prediction II*, the estimated coefficient β_7 should have a negative sign.

3.4.2 Variable measurement

Dependent Variables

Recommendation optimism ($RECO_{i,j,t}$) is defined as the recommendation of broker i on firm j issued at activation date t minus the consensus recommendation. The consensus is cal-

[41] I/B/E/S provides different identifiers for brokerage firms and investment banks, whose analysts issue stock recommendations and target prices. Separate research units (e.g., separate units for small cap and large cap research or national affiliates) of one brokerage firm/investment bank can be identified with the help of the I/B/E/S Broker Code identifier (See Appendix 1 for more details on this aspect). All regression models use, with the exception of the affiliation indicator, the more granular I/B/E/S Broker Code identifier in order to identify brokers on the broker research unit-level. However, it seems implausible that affiliation relationships, and conflicts of interest resulting out of it, are restricted to one research unit within a brokerage firm/investment bank. Thus, the affiliation indicator variable is calculated on the firm level of a brokerage firm/investment bank.

culated by drawing on the most recent recommendations issued by other brokers on the same firm within the last 365 days before activation date t. Definition is analogue to Dubois et al. (2014).

Target price optimism (*TPO* $_{i,j,t}$), which can be considered as the implicit return of target prices, is defined as the ratio of the target price of broker i on firm j issued at activation date t and the concurrent stock price before activation date t of firm j minus one. The concurrent stock price is the latest previous closing stock price obtainable from Datastream before the activation t date of the target price by broker i on firm j. Definition is analogue to Bradshaw et al. (2014). Target price optimism (*TPO* $_{i,j,t}$) is winsorized at the 1% and 99% percentiles.

The Market adjusted cumulative returns (*MAR* $_{j,t}$) of firm j are cumulated over a five-day window around a target price activation date t and by using the respective country specific MSCI Index for market returns. The calculation of the MARs follows Bradley et al. (2003). Moreover, I follow prior research (Asquith et al. 2005; Arand et al. 2015) and use a five-day window.[42]

Independent Variables

In addition to the MAD, MiFiD and Affiliation indicators and the target price revisions (*TP_REV* $_{i,j,t}$), I include additional analyst metric related independent variables in model 2:

First, recommendation upgrade (*REC_UP* $_{i,j,t}$), which is an indicator variable taking the value of one when the stock recommendation by broker i on firm j is an upgrade when compared with the previous stock recommendation issued by the same broker i about the same firm j and otherwise zero. Second, recommendation reiteration (*REC_REIT* $_{i,j,t}$), which is an indicator variable taking the value of one when the stock recommendation by broker i on firm

[42] Other relevant prior studies (e.g., Cornett et al. 2007; Kadan et al. 2009) and current studies (e.g., Hitz and Müller-Bloch 2015) from other research fields applying an event-study design use a more narrow three-day window . However, a broader five-day window should be more robust in cases when stock recommendations and target prices are not activated in I/B/E/S immediately after they were made available to capital market participants via other channels.

j is unchanged when compared with the previous stock recommendation issued by the same broker i about the same firm j and otherwise zero. Third, recommendation downgrade ($REC\_DOWN_{i,j,t}$), which is an indicator variable taking the value of one when the stock recommendation by broker i on firm j is a downgrade, when compared with the previous stock recommendation issued by the same broker i about the same firm j and otherwise zero. The definition of all three variables follows Arand et al. (2015).

Additionally, in order to control for the broker- and firm-specific time-variant characteristics I add, in line with relevant prior studies investigating target prices like Bilinski et al. (2013), Bradshaw et al. (2014) , Arand and Kerl (2015) and Arand et al. (2015) further control variables to my models 1 and 2. My set of control variables includes all those controls included in the baseline-model of Dubois et al. (2014). Furthermore, like Dubois et al. (2014), standard errors are clustered at the broker-level in my regressions. Thus, a replication of their approach in order to validate my identification of affiliated broker firms is possible. Details concerning the construction and data sources of the control variables and the variables outlined above can be found in Table 3.1 and Table 3.2.

Table 3. 1: Regulatory Attributes and Entry-into-Force Dates

Country	Regulatory Attributes				Entry-into-Force Dates	
	Reg-Quality Kaufman (2009)	Pre_MAD Indicator	Sanction Severity	Supervisory Power	MAD	MIFID
Austria	1.52	0	10	70	1-Jan-2005	1-Nov-2007
Belgium	1.36	0	4	69	19-Sep-2005	1-Nov-2007
Denmark	1.79	0	12	60	1-Apr-2005	1-Nov-2007
Finland	1.9	0	12	63	1-Jul-2005	1-Nov-2007
France	1.18	1	4	75	27-Jul-2005	2-Dec-2007
Germany	1.51	1	9	64	30-Oct-2004	1-Nov-2007
Ireland	1.66	n.a.	4	73	6-Jul-2005	21-Nov-2007
Italy	1.02	1	2	70	18-May-2005	28-Nov-2007
Netherlands	1.76	n.a.	7	67	1-Oct-2005	1-Nov-2007
Portugal	1.21	0	7	73	15-Apr-2006	1-Nov-2007
Spain	1.29	1	2	60	24-Nov-2005	17-Feb-2008
Sweden	1.69	0	11	73	1-Jul-2005	1-Nov-2007
UK	1.68	0	1	76	1-Jul-2005	1-Nov-2007

Table 3.1 includes information on the Entry-into-Force-Dates of the MAD and MiFID and Regulatory Attributes. More details concerning the calculation and sources of the Regulatory Attributes can be obtained from Table 3.2. No information for the calculation of the Pre_MAD indicator is avilabale in case of Ireland and the Netherlands. Entry-into-force dates of the MAD and MiFID were obtained from the European Commission website.

Table 3. 2: Definition of Variables

Variable		Definition	Data sources
Dependent variable: Optimism metric			
Recommendation optimism	$RECO_{i,j,t}$	Recommendation of broker i on firm j issued at activation date t minus the consensus recommendation. The consensus is calculated by drawing on the most recent recommendations issued by other brokers on the same firm within the last 365 days before activation date t. Definition is analogue to Dubois et al. (2014).	I/B/E/S
Target price optimism (implicit return)	$TPO_{i,j,t}$	The ratio of the target price of broker i on firm j issued at activation date t and the concurrent stock price before activation date t of firm j minus one. The concurrent stock price is the latest previous closing stock price obtainable from datastream before the activation t date of the target price by broker i on firm j. Definition is analogue to Bradshaw et al. (2014). Target price optimism is winsorized at the 1% and 99% percentiles.	I/B/E/S; Datastream
Target price optimism risk adjusted	$TPO\_adj_{i,j,t}$	Target price optimism (TPO) minus average industry returns over 250 days before activation date t. Industry returns are calculated by country, if at least 5 firms are included within one industry (based on the I/B/E/S industry sector classification (IBSCT) and within one year. Otherwise global industry returns are used. Definition is analogue to Bradshaw et al. (2014). Risk adjusted target price optimism is winsorized at the 1% and 99% percentiles.	I/B/E/S; Datastream
Dependent variable: Event study			
Market adjusted cumulative returns	$MAR_{j,t}$	Market-adjusted returns of firm j, cumulated over a five-day window around a target price activation date t and by using the respective MSCI Index for market returns. Definition is analogue to Bradley et al. (2003).	Datastream

(Table 3.2 continued)

Independent variables: Regulation related			
Reg_Indicator_ 1: Market Abuse Directive	$MAD_{t,c}$	Indicator variable, taking the value of one when a recommendation or target price is released after the Market Abuse Directive has been implemented in a country c and otherwise zero.	European Commission
Reg_Indicator_ 2: Markets in Financial Instruments Directive	$MiFID_{t,c}$	Indicator variable, taking the value of one when a recommendation or target price is released after the Markets in Financial Instruments Directive has been implemented in a country c and otherwise zero.	European Commission
Affiliation	$AFFIL_{i,j,t}$	Indicator variable, taking the value of one, when broker house i, which issued the target price or stock recommendation, acted as an underwriter in equity (IPOs, SEOs), debt-issuances or M&A advisor within the last 365 days before activation date t for the analysed firm j. Definition is analogue to Dubois et al. (2014).	I/B/E/S; SDC
Independent variables: Regulatory Attributes			
Regulatory Quality	REG_Q_{c}	Indicator variable, taking the value of one, when the index value in 2003 of the Regulatory Quality index by Kaufman et al. (2009) in country c is above the sample median and otherwise zero. The index captures "*perceptions of the ability of the government to formulate and implement sound policies and regulations that permit and promote private sector development*" (Kaufmann et al. 2009, p. 6). Approach is analogue to Christensen et al. (2016).	Kaufmann et al. (2009)
Sanction severity of MAD (Ranking)	$SANC\_SEV_{c}$	Indicator variable, taking the value of one when the rank of the sanction severity index by Dubois et al. (2014) in country c is below the sample median and otherwise zero. The sample countries "*are ranked based on their respective administrative pecuniary penalties, criminal sanctions, and fines ([MAD] articles 4, 6.3, 6.5, and 14.3). For each country, the average rank for the three sorts of sanctions is the sanction severity index*" Dubois et al. (2014, p.525). Countries are ranked from 1 (highest sanction severity) to 12 (lowest sanction severity).	Dubois et al. (2014)

(Table 3.2 continued)

Supervisory power	S_POWER_c	Indicator variable, taking the value of one, when the count of positive answers (in a questionnaire answered by European regulators concerning their competences in the case of MAD) is above the sample median and otherwise zero.	Christensen et al. (2016)
Pre MAD Disclosure requirements	Pre_MAD_c	Indicator variable, taking the value of one when the compulsory disclosure of conflicts of interest, caused by underwriting services provided by affiliated brokerage firms, also existed before MAD in country c and otherwise zero. This indicator is based on a review of the pre-MAD regulatory environment provided by the Forum Group (2003).	Forum Group (2003)
Independent variables: Analyst metric related			
Target price revision	$TP\_REV_{i,j,t}$	The percentage change in the target price of broker i at activation date t on firm j when compared with the previous target price issued by the same broker research unit i about the same firm j. Definition is analogue to Arand et al. (2015). Target price revision is winsorized at the 1% and 99% percentiles.	I/B/E/S
Recommendation upgrade	$REC\_UP_{i,j,t}$	Indicator variable, taking the value of one when the recommendation by broker i at activation date t on firm j is an upgrade, when compared with the previous recommendation issued by the same broker research unit i about the same firm j and otherwise zero. Definition is analogue to Arand et al. (2015).	I/B/E/S
Recommendation reiteration	$REC\_REIT_{i,j,t}$	Indicator variable, taking the value of one when the recommendation by broker i at activation date t on firm j is unchanged, when compared with the previous recommendation issued by the same broker research unit i about the same firm j and otherwise zero. Definition is analogue to Arand et al. (2015).	I/B/E/S
Recommendation downgrade	$REC\_DOWN_{i,j,t}$	Indicator variables, taking the value of one when the recommendation by broker i at activation date t on firm j is a downgrade, when compared with the previous recommendation issued by the same broker research unit i about the same firm j and otherwise zero. Definition is analogue to Arand et al. (2015).	I/B/E/S

(Table 3.2 continued)

Independent variables: Control variables			
Herding of stock recommendations	$HERDING_{i,j,t}$	Indicator variable, taking the value of one if a recommendation provided by another broker research unit on the same firm j was activated within 10 days before activation date t (of recommendation of broker research unit i) and both recommendations are either positive ("strong buy" or "buy") or negative ("underperform" or "sell") and otherwise zero. Definition is analogue to Dubois et al. (2014).	I/B/E/S
Initiation of coverage	$INITIATION_{i,j,t}$	Indicator variable, taking the value of one in the case of the first (within the sample period) target price or recommendation of broker research unit i on firm and otherwise zero. Definition is analogue to Dubois et al. (2014).	I/B/E/S
Confounding Earnings Release	$CER_{i,j,t}$	Indicator variable, taking the value of one when earnings of firm j were announced during a window of two days before a stock recommendation or target price of broker research unit i was activated and otherwise zero. Definition is analogue to Dubois et al. (2014).	Worldscope
Market capitalisation	$LOG\_MCAP_{j,t}$	The logarithm of market capitalisation (in Million Euro) of firm j at date t.	Datastream
Market-to-Book Ratio	$LOG\_MB_{j,t}$	The logarithm of the Market-to-Book Ratio of firm j at date t.	Datastream
Prior stock performance	$S\_PERF_{j,t}$	Cumulated daily stock returns of firm j over a 250 day period before date t.	Datastream
Prior stock price standard deviation	$S\_VOL_{j,t}$	Standard deviation of daily stock returns of firm j over a 250 day period before date t.	Datastream
Prior market performance	$M\_PERF_{c,t}$	Cumulated daily stock returns of a country's MSCI market index over a 250 day period before date t.	Datastream
Brokersize	$LOG\_BSIZE_{i,t}$	The logarithm of the number of firms covered by broker research unit i in the year of date t.	I/B/E/S

(Table 3.2 continued)

Coverage intensity	$LOG\_COV_{j,t}$	The logarithm of the number of analysts covering firm j at date t. Number of analysts is the number of estimates included in the I/B/E/S consensus recommendation for firm j at date t.	I/B/E/S
Industry indicator	$IBSCT_j$	Industry indicators are based on the I/B/E/S industry sector classification (IBSCT).	I/B/E/S
Fixed effects structure: broker research units-, industry-, year- and country-fixed effects; Standard errors clustered at the broker research unit-level.			I/B/E/S; Datastream; Worldscope

3.5 Results

3.5.1 Sample construction and descriptive statistics

I examine a sample of I/B/E/S Detail target prices and stock recommendations for firms listed in 13 countries within the European Union. In order to facilitate comparability to the findings of Dubois et al. (2014) I restrict the sample to the same EU-member countries and follow their sample selection criteria as closely as possible.[43]

Analyst target price and stock recommendation data as taken from the I/B/E/S detail database, stock prices and further data was obtained from Datastream and Worldscope. Data about M&A transactions, equity (IPOs, SEOs) and debt issuances were obtained from SDC Platinum. Information concerning sanction severity and other regulatory attributes were obtained from Dubois et al. (2014), Christensen et al. (2016) and from Forum Group (2003). More details concerning the data sources and calculation of the different dependent and independent variables can be found in Table 3.1, Table 3.2 and Appendix I.

Target prices and stock recommendations from I/B/E/S Detail are obtained for listed firms which are included in the Worldscope lists of the relevant EU-countries. My stock recommendations sample includes the period 1997-2007 of Dubois et al. (2014) and is extended

[43] Following Dubois et al. (2014) Greece and Luxembourg are excluded due to poor data coverage in these markets.

until 2011 - in order to investigate the impact of the MiFID. There are hardly any target prices available for firms listed in the relevant EU-member countries in the years before 2003, thus the sample period of my target price sample includes the years 2003 until 2011.[44]

Following Dubois et al. (2014), firms in the target price and stock recommendation sample are assigned to the sample country, in which they are primarily listed. Moreover, also in line with Dubois et al. (2014), firms, which are not incorporated and primarily listed in the same country, are excluded both from the target price and stock recommendation sample. Moreover, following Dubois et al. (2014), unusual patterns of stock recommendations issues are accounted for by identifying and excluding all those recommendations. This is done by excluding all recommendations by the same brokerage on one specific day, if more than 200 stock recommendations were issued by the same brokerage firm on that day. Such an unusual pattern of recommendation issues might be caused by changes in the stock recommendation rating system (Dubois et al. 2014, pp.499-500)[45]. Also in line with Dubois et al. (2014), the original I/B/E/S rating system ("*Strong buy*" is dedicated to the number "1", "*Buy*" to the number "2" etc.) is reversed ("*Strong buy*" is dedicated to the number "5", "*Buy*" to the number "4" etc.) in order to increase the comprehensibility of the rating system.

Following Bilinski et al. (2013), in order to ensure comparability, I retain only target prices with a stated 12-month forecast horizon in the sample. Moreover, also following Bilinski et al. (2013), target prices, whose currency at firm level from I/B/E/S ("*default currency*") is different from the currency of stock prices obtained from Datastream, are excluded from the sample.[46] Moreover, also following Bilinski et al. (2013), market capitalisation is expressed

[44] Similarly, Bradshaw et al. (2014) assert their sample of target prices, which includes target prices issued by analysts from 44 different countries, to be dominated by target prices issued on US-firms before the year 2002. Thus, the authors do not include target prices issued before the year 2002. Bilinski et al. (2013) do not include target prices issued before the year 2002 in their sample, too.

[45] See also Kadan et al. (2009) for more details concerning changes in stock recommendation rating systems caused by regulatory reforms.

[46] See also Thomson Reuters (2010) for more information concerning the reporting and currency translation practice in I/B/E/S detail data: If target prices are provided in different currencies for a company, Thomson Reuters translates them into the consistent firm-level default currency of the company.

uniformly in one currency (Euro) for all firms. The samples were further reduced due to missing data in I/B/E/S, Datastream and Worldscope. Ultimately, 354344 target prices, issued within the years 2003-2011, and 378753 stock recommendations, issued within the years 1997-2011, could be obtained.

Table 3.3 provides descriptive statistics, Panel A includes the stock recommendation sample and Panel B the target price sample. Descriptive statistics in Table 3.3 are based on the baseline regressions (stock recommendations: regressions 1-4 in Table 3.7, the consensus in RECO requires at least 1 recommendation here; target prices: regression 2-4 in Table 3.8). The samples were further reduced in the regression specifications, due to data limitations.[47] As can be seen in Table 3.3, about 3,9% of the observations in the case of the stock recommendations and 5,4% in the case of the target prices are categorized as affiliated, which is a slightly higher proportion than in Dubois et al. (2014), who have a proportion of 2,2% affiliated stock recommendations in their sample. Table 3.4 provides pearson‘s correlation coefficients for both samples. Tables 3.5 and 3.6 provide further details concerning the sample composition and distribution of stock recommendations and target prices.

[47] Due to missing data, a minimum requirement in the consensus in RECO, exclusion of target prices and stock recommendations which do not have a previous target price and recommendation by the same broker research unit for the same company and exclusion of target price revisions which do not take place within 90 days (following Arand et al. 2015).

Table 3. 3: Descriptive Statistics

Table 3.3, Panel A: Descriptive Statistics – Stock Recommendation Sample

	mean	min	p25	p50	p75	max
RECO	-0.052	-4.000	-0.793	0.000	0.750	4.000
MAD	0.449	0.000	0.000	0.000	1.000	1.000
MIFID	0.288	0.000	0.000	0.000	1.000	1.000
AFFIL	0.039	0.000	0.000	0.000	0.000	1.000
HERDING	0.166	0.000	0.000	0.000	0.000	1.000
CER	0.017	0.000	0.000	0.000	0.000	1.000
INITIATION	0.183	0.000	0.000	0.000	0.000	1.000
S_PERF	0.093	-0.999	-0.218	0.043	0.308	48.205
M_PERF	0.055	-0.751	-0.132	0.085	0.215	2.170
LOG_BSIZE	5.091	0.000	4.454	5.136	5.829	6.788
LOG_COV	2.576	0.000	2.079	2.708	3.135	3.989

Table 3.3, Panel B: Descriptive Statistics – Target Price Sample

	mean	min	p25	p50	p75	max
TPO	0.179	-0.353	0.017	0.127	0.256	1.957
MAD	0.908	0.000	1.000	1.000	1.000	1.000
MIFID	0.683	0.000	0.000	1.000	1.000	1.000
AFFIL	0.054	0.000	0.000	0.000	0.000	1.000
CER	0.034	0.000	0.000	0.000	0.000	1.000
S_PERF	0.078	-0.995	-0.245	0.045	0.317	24.571
M_PERF	0.014	-0.751	-0.165	0.072	0.178	0.758
LOG_BSIZE	5.470	0.000	4.836	5.642	6.227	6.648
LOG_COV	2.608	0.000	2.197	2.773	3.178	3.989
TP_REV	0.011	-0.577	-0.087	0.010	0.095	0.806
LOG_MCAP	7.583	-1.897	6.343	7.606	8.872	12.071
LOG_MB	0.606	-4.605	0.095	0.582	1.065	6.753
S_VOL	0.024	0.000	0.016	0.021	0.028	0.956

Table 3.3 Panel A shows the descriptive statistics for both continuous and indicator variables included in the baseline stock recommendation sample (years in sample 1997-2011). Panel B shows the descriptive statistics for continuous and indicator variables included in the baseline target price sample (years in sample 2003-2011). Descriptive statistics in Table 3.3 are based on the baseline regressions (stock recommendations: regressions 1-4 in Table 3.7, the consensus in RECO requires at least 1 recommendation; target prices: regression 2-4 in Table 3.8).

Table 3. 4: Correlation Matrix

Table 3.4, Panel A: Pearson’s correlation coefficients for variables in the Stock Recommendation Sample

		1	2	3	4	5	6	7	8	9	10	11
RECO	1	1.00										
MAD	2	-0.01**	1.00									
AFFIL	3	0.01***	0.01***	1.00								
MIFID	4	-0.01***	0.71***	0.01***	1.00							
INITIATION	5	0.02***	-0.15***	-0.04***	-0.09***	1.00						
HERDING	6	0.16***	0.01***	0.02***	0.01***	-0.02***	1.00					
CER	7	-0.00	0.03***	0.00*	0.03***	-0.02***	0.02***	1.00				
S_PERF	8	0.02***	-0.02***	0.00	-0.13***	0.06***	0.00*	0.01***	1.00			
M_PERF	9	0.02***	-0.12***	-0.01***	-0.29***	0.12***	-0.02***	0.01***	0.50***	1.00		
LOG_BSIZE	10	-0.05***	-0.13***	0.11***	-0.09***	-0.08***	-0.02***	0.01***	-0.05***	-0.07***	1.00	
LOG_COV	11	-0.00	-0.02***	0.08***	-0.00	-0.08***	0.12***	-0.02***	-0.05***	0.00	0.00	1.00

(continued)

(Table 3.4 continued)

Table 3.4, Panel B: Pearson's correlation coefficients for variables in the Target Price Sample

		1	2	3	4	5	6	7	8	9	10	11	12	13
TPO	1	1.00												
MAD	2	0.04***	1.00											
MIFID	3	0.11***	0.47***	1.00										
AFFILL	4	0.03***	-0.01***	-0.01**	1.00									
CER	5	-0.01**	0.02***	0.02***	-0.00	1.00								
S_PERF	6	-0.12***	-0.08***	-0.22***	-0.00	0.03***	1.00							
M_PERF	7	-0.14***	-0.13***	-0.41***	0.01***	0.04***	0.60***	1.00						
LOG_BSIZE	8	-0.07***	-0.14***	-0.15***	0.12***	0.01***	-0.01***	0.02***	1.00					
LOG_COV	9	-0.09***	-0.04***	-0.02***	0.08***	-0.01***	-0.04***	0.02***	0.20***	1.00				
TP_REV	10	-0.01***	-0.07***	-0.15***	-0.01***	0.01***	0.41***	0.30***	0.00	0.00	1.00			
LOG_MCAP	11	-0.10***	-0.04***	-0.12***	0.14***	-0.01***	0.09***	0.11***	0.20***	0.81***	0.09***	1.00		
LOG_MB	12	-0.09***	-0.07***	-0.26***	-0.06***	0.01***	0.29***	0.26***	0.05***	0.06***	0.18***	0.14***	1.00	
S_VOL	13	0.11***	0.13***	0.35***	0.01***	-0.00**	-0.13***	-0.36***	-0.08***	-0.13***	-0.06***	-0.28***	-0.30***	1.00

Table 3.4 Panel A shows the Pearson's correlation coefficients for variables included in the stock recommendation sample (years in sample 1997-2011). Panel B shows the Pearson's correlation coefficients for variables included in the baseline target price sample (years in sample 2003-2011). Correlations in Table 3.4 are based on the baseline regressions (stock recommendations: regressions 1-4 in Table 3.7, the consensus in RECO requires at least 5 recommendation; target prices: Regression 2-4 in Table 3.8). The reported values are the coefficients (and t-values in brackets). ***, ** and * indicate significance (two-tailed) at the 1%, 5% and 10% level.

Table 3. 5: Composition Stock Recommendation Sample

Table 3.5 Panel A: Stock Recommendation Sample composition - sorted by country

	Recommendations (REC)	Affiliated REC	Number of broker units	Number of firms
Austria	4546	355	124	119
Belgium	10650	442	146	177
Denmark	10168	428	136	186
Finland	16276	431	150	165
France	57664	3791	238	919
Germany	58969	2692	255	904
Ireland	2445	94	89	78
Italy	24443	1547	172	392
Netherlands	27276	906	181	243
Portugal	5982	236	92	76
Spain	22254	1043	165	183
Sweden	23394	990	171	396
United Kingdom	114686	4363	308	2918
Total	378753	17318	n.a.	6756

Table 3.5 Panel B: Stock Recommendation Sample composition - sorted by year

	Recommendations (REC)	Affiliated REC	Number of broker units	Number of firms
1997	25494	764	191	2791
1998	27295	900	191	2907
1999	25963	1137	188	2991
2000	22026	1216	163	2867
2001	26031	1475	140	2848
2002	25170	1033	130	2489
2003	24708	1084	138	2375
2004	22556	1049	157	2409
2005	25538	1206	174	2616
2006	24464	1224	183	2736
2007	26229	1490	200	2922
2008	27583	1187	229	2864
2009	29000	1209	242	2642
2010	23058	1206	245	2471
2011	23638	1138	254	2387
Total	378753	17318	n.a.	n.a.

Table 3.5 Panel A provides information about the stock recommendation sample composition - sorted by country, Panel B provides information about the stock recommendation sample composition - sorted by year.

Table 3. 6: Composition Target Price sample

Table 3.6 Panel A: Target Price Sample composition - sorted by country

	Target prices	Affiliated target prices	Number of broker units	Number of firms
Austria	5660	451	96	61
Belgium	10005	432	89	123
Denmark	10925	517	79	100
Finland	16395	435	89	127
France	57806	4927	155	591
Germany	56961	2837	164	626
Ireland	2183	126	58	38
Italy	29238	2509	96	295
Netherlands	20176	923	115	140
Portugal	3873	200	58	36
Spain	24832	1341	99	155
Sweden	25431	1069	101	297
United Kingdom	90859	4453	183	1672
Total	354344	20220	n.a.	4261

Table 3.6 Panel B: Target Price Sample composition - sorted by year

	Target prices	Affiliated target prices	Number of broker units	Number of firms
2003	9657	672	29	1272
2004	19085	1052	71	1794
2005	23728	1274	96	2132
2006	33972	2110	118	2290
2007	38823	2649	144	2557
2008	55753	2859	206	2880
2009	58574	2807	237	2742
2010	56295	3416	231	2620
2011	58457	3381	249	2611
Total	354344	20220	n.a.	n.a.

Table 3.6 Panel A provides information about the target price sample composition - sorted by country, Panel B provides information about the target price sample composition - sorted by year.

3.5.2 Empirical findings

Stock recommendations optimism: Replication of Dubois et al. (2014)

Table 3.7 reports the results of the stock recommendations optimism regressions with different regression specifications and sample periods (models 1-4). Moreover, Table 3.7 contains, as a comparison, the results of the baseline model of (model 1 in Table III, Dubois et al. (2014, p. 508). In order to verify my affiliation identification approach, I replicate the baseline model of Dubois et al. (2014) with the help of model 1 in Table 3.7, which includes the same set of explanatory variables, fixed effects and is estimated for the same sample period.[48] Affiliation (*AFFIL*) and the interaction term *MAD×AFFIL* have the same signs and are significant in both the original and the replication model 1. However, *MAD×AFFIL* is significant only at the 10% level in model 1. Moreover, the significant control variables *HERDING* and *LOG_COV* have a different sign in the replication. Furthermore, although the same sample selection criteria were applied, the sample size in my replication is smaller (261260 vs. 202856 observations).

Model 2 is estimated for a shorter sample period, beginning with the year 2003 and thus runs parallel to the sample period of the target price sample. Models 3 and 4 are estimated for the long sample period 1997-2011. Affiliation (*AFFIL*) has a positive and higly significant impact in all four models 1-4. Moreover, the interaction terms *MAD×AFFIL* (in model 3) and *MIFID×AFFIL* (in model 4) are significant at the 5% level and have a negative sign in both cases.

[48] I replicate the relevant regression of Dubois et al. (2014) as closely as possible. There remain small differences in the specification of my control variables LOG_BSIZE (which is calculated within a year in my sample, not over the year before a date t) and LOG_COV (which is calculated on the basis of the number of estimates included in the I/B/E/S consensus recommendation in my sample).

Target price optimism: Test of Prediction I

Table 3.8 reports the results of the target price optimism regressions with different regression specifications and sample periods (models 1-4). Model 1 and 2 are estimated for a shorter pre-MiFID period, while models 3 and 4 include the years 2003-2011 and thus include the post-MiFID period. Moreover, model 1 narrowly replicates the controls and fixed-effects structure of Dubois et al. (2014)[49], while models 2-4 include further relevant controls and industry fixed-effects. In all models 1-4, the interaction terms *MAD×AFFIL* and *MIFID×AFFIL* respectively are highly significant and have the predicted positive sign. Affiliation (*AFFIL*) by itself does have a significant impact only in model 4, while the MAD and MiFID indicators do have a significant positive impact on all models. The signs of the control variables are largely, with the exception of LOG_MCAP in Model 2, in line with relevant prior research (e.g., Bradshaw et al. 2014; Arand and Kerl 2015).

Event study: Test of Prediction II

Table 3.9 reports the results of the event study regressions with different regression specifications and sample periods (models 1-4). Following Arand et al. (2015), the sample is restricted to target prices, which were revised within a 90 day window. Moreover, the regression models control for confounding stock recommendation changes, which take place on the same date. Revisions of target prices (*TP_REV*) do have a significant impact on Market Adjusted Returns (MAR) in all three models. The interaction terms *MAD×TP_REV* and *MIFID×TP_REV* are highly significant and have a positive sign in all three regression specifications, indicating that revisions of target prices have a stronger impact on MARs in the post-regulation period. Moreover, the interaction term *TP_REV×AFFIL* has a significant positive impact on MARs in the models 1 and 2, which indicates that target price revisions issued by affiliated broker firms had a stronger impact in der pre-regulation period. However, the inter-

[49] Except HERDING, which is a stock recommendation specific variable.

action terms *MAD×TP_REV×AFFIL* and *MIFID×TP_REV×AFFIL* remain insignificant. This indicates, that there is no incremental impact of the regulatory measures on affiliated analysts relative to unaffiliated analysts. The total effect on affiliated analysts in these regression specifications can be captured by summing up the coefficients β_5 *RegIndicator* × *Affiliation* + β_7 *RegIndicator* × *TP_REV*× *Affiliation* .

Table 3. 7: Stock Recommendations Optimism (RECO) Regressions

	Results of Dubois et al. (2014)	(1)	(2)	(3)	(4)
Sample Period	1997-2007	1997-2007	2003-2007	1997-2011	1997-2011
AFFIL	0.243***	0.123***	0.130***	0.133***	0.118***
	(11.02)	(7.05)	(5.17)	(6.97)	(8.05)
MAD	0.019	-0.022	-0.025	-0.025	-0.028
	(0.83)	(-0.84)	(-1.06)	(-0.86)	(-0.97)
MADxAFFIL	-0.213***	-0.063*	-0.046	-0.066**	
	(6.74)	(-1.90)	(-1.28)	(-2.41)	
MIFID				-0.089***	-0.087***
				(-3.24)	(-3.20)
MIFIDxAFFIL					-0.050**
					(-1.99)
HERDING	-0.028***	0.428***	0.365***	0.420***	0.420***
	(5.06)	(34.66)	(23.60)	(37.36)	(37.38)
CER	0.009	-0.039**	-0.055**	-0.044***	-0.044***
	(0.50)	(-1.99)	(-1.99)	(-2.59)	(-2.59)
INITIATION	0.087***	0.041***	0.061***	0.052***	0.052***
	(7.20)	(3.52)	(3.72)	(4.60)	(4.59)
S_PERF	0.004	-0.011	-0.026	-0.004	-0.004
	(0.62)	(-1.16)	(-1.45)	(-0.45)	(-0.45)
M_PERF	0.017	0.145***	0.315***	0.143***	0.143***
	(0.60)	(4.64)	(5.38)	(5.50)	(5.50)
LOG_BSIZE	-0.036***	-0.048*	-0.029	-0.037	-0.038
	(3.58)	(-1.81)	(-0.92)	(-1.63)	(-1.63)
LOG_COV	0.092***	-0.027*	0.015	-0.013	-0.013
	(3.99)	(-1.78)	(0.78)	(-1.02)	(-1.02)
Fixed-Effects-Structure	Broker/Year/Country	Broker/Year/Country	Broker/Year/Country	Broker/Year/Country/Industry	Broker/Year/Country/Industry
Observations	261260	202856	92154	284049	284049
R^2	0.04	0.058	0.061	0.057	0.057
Adjusted R^2	n.a.	0.056	0.058	0.055	0.055

(continued)

(Table 3.7 continued)

Notes: The relevant regression model is:

$RECO = \beta_0 + \beta_1 \, RegIndicator + \beta_2 \, Affiliation + \beta_3 \, RegIndicator{\times}Affiliation + \sum \beta_j \, Controls_j + \sum \beta_j \, Fixed\ Effects_j + \varepsilon$

The indicator variable *RegIndicator×Affiliation* measures the DiD-effect, the impacts of the introduction of the RegIndicator (MAD or MiFID) on analyst stock recommendation optimism (RECO) of affiliated broker firms. For the definition of the variables, see Table 3.2. Moreover, this table contains, as a comparison, the results of model 1 in Table III of Dubois et al. (2014, p. 508). The consensus in RECO of the regression models (1)-(4) and of model 1 in Table III of Dubois et al. (2014, p. 508) requires at least 5 recommendations. The regression models include broker-, country-, industry- and year-fixed effects, if indicated. Standard errors are clustered at the broker-level. The reported values are the coefficients (and t-values in brackets). ***, ** and * indicate significance (two-tailed) at the 1%, 5% and 10% level, respectively.

Table 3. 8: Target Price Optimism (TPO) Regressions

	(1)	(2)	(3)	(4)
Sample Period	2003-2007	2003-2007	2003-2011	2003-2011
AFFIL	-0.003	-0.000	0.007	0.020***
	(-0.51)	(-0.05)	(0.90)	(2.70)
MAD	0.008*	0.008*	0.013**	0.016**
	(1.84)	(1.70)	(2.08)	(2.54)
MADxAFFIL	0.025***	0.025***	0.048***	
	(2.68)	(2.71)	(5.88)	
MIFID			0.050***	0.048***
			(9.41)	(8.53)
MIFIDxAFFIL				0.045***
				(5.10)
CER	-0.013***	-0.016***	0.000	0.000
	(-2.69)	(-3.03)	(0.07)	(0.07)
INITIATION	0.016*			
	(1.95)			
LOG_BSIZE	0.003	-0.008	-0.001	-0.001
	(0.29)	(-0.72)	(-0.08)	(-0.13)
LOG_COV	-0.014***	-0.018***	-0.030***	-0.030***
	(-3.07)	(-3.63)	(-7.11)	(-7.12)
S_PERF	-0.039***	-0.074***	-0.051***	-0.050***
	(-6.06)	(-8.03)	(-10.51)	(-10.40)
M_PERF	-0.203***	-0.136***	-0.116***	-0.117***
	(-7.98)	(-6.98)	(-12.29)	(-12.39)
S_VOL		1.819***	1.851***	1.843***
		(5.61)	(8.01)	(7.98)
LOG_MCAP		0.006***	0.002	0.002
		(2.94)	(1.45)	(1.45)
LOG_MB		-0.006*	-0.026***	-0.026***
		(-1.82)	(-9.71)	(-9.74)
TP_REV		0.168***	0.137***	0.137***
		(12.04)	(15.24)	(15.22)
Fixed-Effects-Structure	Broker/Year/ Country	Broker/Year/ Country/ Industry	Broker/Year/ Country/ Industry	Broker/Year/ Country/ Industry
Observations	121081	100719	305208	305208
R^2	0.042	0.051	0.092	0.093
Adjusted R^2	0.040	0.050	0.091	0.092

(continued)

(Table 3.8 continued)

Notes: The relevant regression model is:

$TPO = \beta_0 + \beta_1\, RegIndicator + \beta_2\, Affiliation + \beta_3\, RegIndicator{\times}Affiliation + \sum \beta_j\, Controls_j + \sum \beta_j\, Fixed\ Effects_j + \varepsilon$

The indicator variable *RegIndicator×Affiliation* measures the DiD-effect, the impacts of the introduction of the MAD or MiFID (RegIndicator) on analyst target price optimism (TPO) of affiliated broker firms. For the definition of the variables, see Table 3.2.The regression models include broker-, country-, industry- and year-fixed effects, if indicated. Standard errors are clustered at the broker-level. The reported values are the coefficients (and t-values in brackets). ***, ** and * indicate significance (two-tailed) at the 1%, 5% and 10% level.

Table 3. 9: Event Study Regressions

	(1)	(2)	(3)
Sample Period	2003-2007	2003-2011	2003-2011
AFFIL	-0.005	-0.006	-0.002
	(-1.28)	(-1.61)	(-0.80)
TP_REV	0.050***	0.044***	0.083***
	(4.95)	(4.42)	(7.49)
REC_UP	0.004	0.008***	0.009***
	(1.14)	(6.02)	(6.43)
REC_DOWN	-0.015***	-0.015***	-0.015***
	(-5.20)	(-8.16)	(-7.95)
TP_REVxAFFIL	0.052**	0.053**	0.012
	(2.14)	(2.26)	(0.49)
MAD	-0.004	-0.003	0.002
	(-1.62)	(-1.52)	(0.94)
MADxAFFIL	0.004	0.007	
	(0.69)	(1.29)	
MADxTP_REV	0.067***	0.073***	
	(6.19)	(7.97)	
MADxTP_REVxAFFIL	-0.057	-0.051	
	(-1.20)	(-1.09)	
MIFID		0.000	-0.001
		(0.06)	(-0.23)
MIFIDxAFFIL			0.003
			(0.47)
MIFIDxTP_REV			0.036***
			(3.41)
MIFIDxTP_REVxAFFIL			-0.008
			(-0.17)
Fixed-Effects-Structure	Broker/Year/ Country/ Industry	Broker/Year/ Country/ Industry	Broker/Year/ Country/ Industry
Controls	yes	yes	yes
Observations	9870	28548	28548
R^2	0.170	0.177	0.176
Adjusted R^2	0.158	0.169	0.168

(continued)

(Table 3.9 continued)

Notes: The relevant regression model is:

$MAR = \beta_0 + \beta_1\, RegIndicator + \beta_2\, TP\_REV + \beta_3\, Affiliation + \beta_4\, RegIndicator \times TP\_REV + \beta_5\, RegIndicator \times Affiliation + \beta_6\, TP\_REV \times Affiliation + \beta_7\, RegIndicator \times TP\_REV \times Affiliation + \sum \beta_j\, Controls_j + \sum \beta_j\, Fixed\ Effects_j + \varepsilon$

The indicator *RegIndicator* × *TP_REV* × *Affiliation* measures the variation in the impact of revisions of the target prices (*TP_REV*) caused by the treatment (*RegIndicator:* introduction of the MAD or MiFID), issued by broker firms which are part of the treatment group (affiliated broker firms). For the definition of the variables, see Table 3.2. The sample is restricted to target prices, which were revised within a 90 day window. The regression models include relevant controls (CER S_PERF M_PERF LOG_MCAP LOG_MB), broker-, country-, industry- and year-fixed effects, if indicated. Standard errors are clustered at the broker-level. The reported values are the coefficients (and t-values in brackets). ***, ** and * indicate significance (two-tailed) at the 1%, 5% and 10% level.

3.5.3 Discussion of findings

In a first step, I replicate the baseline model of Dubois et al. (2014, model 1 in Table III, p. 508) in order to validate my affiliation identification approach. I can find comparable results in my regressions specifications. As in the study of Dubois et al. (2014), the MAD had a mitigating impact on affiliated analysts' over-optimism in stock recommendations. However, in my sample, this impact is not highly significant. In the target price optimism regressions I find there is a highly significant positive impact of the regulatory measures on target price optimism, which is in line with my *Prediction I*. My results provide evidence that analysts use their quantitative metrics in different ways. Moreover, these results imply that target prices are an eligible measure for sending overly optimistic signals to investors in the post-regulation period. The results of the MAR regressions include insignificant interaction terms *MAD×TP_REV×AFFIL* and *MIFID×TP_REV×AFFIL* as in Table 3.9. This result is not in line with *Prediction II*, since it predicted a reduced informativeness of affiliated target price revisions in the post regulation period for the case when investors are able to account for the incentives of affiliated analysts. Thus, the results of the MAR regressions imply that market participants cannot look through the incentives of affiliated analysts thoroughly in the post-regulation period, since they do not discount the target price revisions. In conclusion, my results can be interpreted as an indication of an "*avoidance strategy*" (Leuz and Wysocki 2016, p. 536) applied by financial analysts, who have an economic incentive to bias their research outputs even in the post-regulation period. Due to the disclosure requirements of the MAD, which are geared more explicitly towards stock recommendations, it is less risky for financial analysts to bias their target prices instead of stock recommendations in the post-regulation period. This practice is not mitigated by the organizational requirements and conduct-of-business rules, which were introduced by the MiFID.

3.5.4 Robustness tests

Three different tests are applied in order to evaluate the robustness of my regression results. First, by following Bradshaw et al. (2014), a modified target price optimism variable, which is adjusted for risk (*TPO_adj*), is calculated (see details concerning calculation of the variable in Table 3.2). The results of the risk adjusted target price optimism regressions are reported in Table 3.10. While the interaction terms *MAD×AFFIL* become insignificant in the model 1 and model 2, *MAD×AFFIL* and *MIFID×AFFIL* remain highly significant with positive signs in models 3 and 4.

Second, as can be seen in Table 3.6, Panel B, the target price sample is unbalanced, since the number of target prices contained in the sample per year increases with time. Thus, I determine a more balanced sample by restricting the sample to target prices issued by broker houses and to firms, which were both already included in the sample before 2006. The results which target price optimism regressions in the balanced sample are reported in Table 3.11. The results remain largely unchanged, the significance level of the interaction term *MAD×AFFIL* is reduced to the 5% level in model 1 and model 2.

Third, I follow Arand et al. (2015) and restrict the sample to target prices, which were revised within a 90 day window in order to avoid stale information in the sample and to ensure that target prices have sufficiently short intervals. This is required for the exploitation of the identification strategy using the staggered implementation of the MAD (Christensen et al. 2016). The results target price optimism regressions in the 90 day window sample are reported in Table 3.12. The results remain largely unchanged.

Table 3. 10: Risk adjusted Target Price Optimism (TPO) Regressions

	(1)	(2)	(3)	(4)
Sample Period	2003-2007	2003-2007	2003-2011	2003-2011
AFFIL	0.010	0.006	0.012	0.016*
	(1.20)	(0.63)	(1.11)	(1.91)
MAD	0.014**	0.013**	0.027***	0.029***
	(2.37)	(2.07)	(3.30)	(3.61)
MADxAFFIL	0.015	0.016	0.045***	
	(1.11)	(1.04)	(4.10)	
MIFID			0.091***	0.088***
			(9.57)	(9.07)
MIFIDxAFFIL				0.055***
				(5.69)
CER	-0.016***	-0.019***	-0.004	-0.004
	(-2.79)	(-2.78)	(-0.92)	(-0.91)
INITIATION	0.013			
	(1.23)			
LOG_BSIZE	-0.006	-0.020	0.012	0.012
	(-0.48)	(-1.33)	(0.78)	(0.74)
LOG_COV	-0.014***	-0.012*	-0.021***	-0.021***
	(-2.75)	(-1.93)	(-4.77)	(-4.78)
S_PERF	-0.403***	-0.452***	-0.406***	-0.406***
	(-18.46)	(-15.61)	(-34.28)	(-34.29)
M_PERF	-0.908***	-0.784***	-0.848***	-0.849***
	(-18.20)	(-16.79)	(-37.17)	(-37.33)
S_VOL		4.258***	2.867***	2.856***
		(10.33)	(9.23)	(9.14)
LOG_MCAP		0.009***	-0.000	-0.000
		(3.49)	(-0.08)	(-0.08)
LOG_MB		-0.017***	-0.028***	-0.028***
		(-3.31)	(-9.13)	(-9.14)
TP_REV		0.086***	0.079***	0.079***
		(3.26)	(7.02)	(7.01)
Fixed-Effects-Structure	Broker/Year/ Country	Broker/Year/ Country/ Industry	Broker/Year/ Country/ Industry	Broker/Year/ Country/ Industry
Observations	121081	100719	305208	305208
R^2	0.328	0.335	0.555	0.556
Adjusted R^2	0.327	0.334	0.555	0.555

(continued)

(Table 3.10 continued)

Notes: The relevant regression model is:

$TPO\_adj = \beta_0 + \beta_1\,RegIndicator + \beta_2\,Affiliation + \beta_3\,RegIndicator{\times}Affiliation + \sum \beta_j\,Controls_j + \sum \beta_j\,Fixed\ Effects_j + \varepsilon$

The indicator variable *RegIndicator×Affiliation* measures the DiD-effect, the impacts of the introduction of the MAD or MiFID (RegIndicator) on analyst target price optimism (TPO) of affiliated broker firms. For the definition of the variables, see Table 3.2. The regression models include broker-, country-, industry- and year-fixed effects, if indicated. Standard errors are clustered at the broker-level. The reported values are the coefficients (and t-values in brackets). ***, ** and * indicate significance (two-tailed) at the 1%, 5% and 10% level.

Table 3. 11: Target Price Optimism (TPO) Regressions: Balanced Sample

	(1)	(2)	(3)	(4)
Sample Period	2003-2007	2003-2007	2003-2011	2003-2011
AFFIL	-0.005	-0.001	0.004	0.015**
	(-0.74)	(-0.18)	(0.45)	(2.02)
MAD	0.009**	0.010**	0.014**	0.016***
	(2.16)	(1.99)	(2.32)	(2.74)
MADxAFFIL	0.021**	0.022**	0.039***	
	(2.22)	(2.31)	(4.91)	
MIFID			0.050***	0.048***
			(8.15)	(7.59)
MIFIDxAFFIL				0.036***
				(4.16)
CER	-0.011**	-0.013**	-0.002	-0.002
	(-2.23)	(-2.56)	(-0.49)	(-0.50)
INITIATION	0.018**			
	(1.99)			
LOG_BSIZE	0.000	-0.011	0.001	0.000
	(0.04)	(-0.98)	(0.08)	(0.03)
LOG_COV	-0.009*	-0.013**	-0.016***	-0.016***
	(-1.88)	(-2.63)	(-3.65)	(-3.65)
S_PERF	-0.041***	-0.077***	-0.052***	-0.052***
	(-5.61)	(-7.69)	(-8.08)	(-7.99)
M_PERF	-0.199***	-0.128***	-0.103***	-0.103***
	(-7.73)	(-6.80)	(-10.62)	(-10.73)
S_VOL		1.679***	1.736***	1.727***
		(5.71)	(6.99)	(6.96)
LOG_MCAP		0.006***	0.005***	0.005***
		(2.96)	(2.76)	(2.75)
LOG_MB		-0.005	-0.023***	-0.023***
		(-1.41)	(-7.52)	(-7.53)
TP_REV		0.166***	0.130***	0.130***
		(11.77)	(13.03)	(13.01)
Fixed-Effects-Structure	Broker/Year/ Country	Broker/Year/ Country/ Industry	Broker/Year/ Country/ Industry	Broker/Year/ Country/ Industry
Observations	113014	95276	216142	216142
R^2	0.039	0.049	0.068	0.068
Adjusted R^2	0.038	0.048	0.067	0.067

(continued)

(Table 3.11 continued)

Notes: The relevant regression model is:

$TPO = \beta_0 + \beta_1 \, RegIndicator + \beta_2 \, Affiliation + \beta_3 \, RegIndicator \times Affiliation + \sum \beta_j \, Controls_j + \sum \beta_j \, Fixed\ Effects_j + \varepsilon$

The indicator variable *RegIndicator×Affiliation* measures the DiD-effect, the impacts of the introduction of the MAD or MiFID (RegIndicator) on analyst target price optimism (TPO) of affiliated broker firms. For the definition of the variables, see Table 3.2. The sample consists of target prices issued by broker houses about firms, which were both already included in the sample before 2006. The regression models include broker-, country-, industry- and year-fixed effects, if indicated. Standard errors are clustered at the broker-level. The reported values are the coefficients (and t-values in brackets). ***, ** and * indicate significance (two-tailed) at the 1%, 5% and 10% level.

Table 3. 12: Target Price Optimism (TPO) Regressions – within 90 day revision window

	(1)	(2)	(3)	(4)
Sample Period	2003-2007	2003-2007	2003-2011	2003-2011
AFFIL	-0.015*	-0.014*	-0.009	0.011
	(-1.93)	(-1.93)	(-1.11)	(1.62)
MAD	0.015**	0.015**	0.017**	0.021***
	(2.23)	(2.35)	(2.28)	(2.71)
MADxAFFIL	0.034***	0.038***	0.065***	
	(4.00)	(4.59)	(6.28)	
MIFID			0.047***	0.043***
			(6.81)	(6.04)
MIFIDxAFFIL				0.055***
				(5.56)
CER	-0.009	-0.011	0.004	0.004
	(-1.51)	(-1.61)	(1.04)	(1.05)
INITIATION	0.000			
	(.)			
LOG_BSIZE	-0.015	-0.015	0.001	0.000
	(-1.20)	(-1.20)	(0.05)	(0.00)
LOG_COV	-0.014***	-0.021***	-0.029***	-0.029***
	(-2.87)	(-3.56)	(-6.89)	(-6.91)
S_PERF	-0.023***	-0.055***	-0.032***	-0.032***
	(-3.42)	(-6.76)	(-7.59)	(-7.46)
M_PERF	-0.144***	-0.150***	-0.106***	-0.107***
	(-4.49)	(-4.83)	(-8.45)	(-8.52)
S_VOL		1.232***	1.587***	1.578***
		(4.53)	(5.62)	(5.61)
LOG_MCAP		0.006**	0.004**	0.004**
		(2.37)	(2.00)	(2.00)
LOG_MB		-0.004	-0.028***	-0.028***
		(-1.04)	(-8.18)	(-8.20)
TP_REV		0.219***	0.176***	0.176***
		(12.47)	(16.35)	(16.32)
Fixed-Effects-Structure	Broker/Year/ Country	Broker/Year/ Country/ Industry	Broker/Year/ Country/ Industry	Broker/Year/ Country/ Industry
Observations	58568	57210	180153	180153
R^2	0.034	0.052	0.084	0.084
Adjusted R^2	0.031	0.049	0.082	0.083

(continued)

(Table 3.12 continued)

Notes: The relevant regression model is:

$TPO = \beta_0 + \beta_1\, RegIndicator + \beta_2\, Affiliation + \beta_3\, RegIndicator{\times}Affiliation + \sum \beta_j\, Controls_j + \sum \beta_j\, Fixed\ Effects_j + \varepsilon$

The indicator variable *RegIndicator×Affiliation* measures the DiD-effect, the impacts of the introduction of the MAD or MiFID (RegIndicator) on analyst target price optimism (TPO) of affiliated broker firms. For the definition of the variables, see Table 3.2. The sample is restricted to target prices, which were revised within a 90 day window. The regression models include broker-, country-, industry- and year-fixed effects, if indicated. Standard errors are clustered at the broker-level. The reported values are the coefficients (and t-values in brackets). ***, ** and * indicate significance (two-tailed) at the 1%, 5% and 10% level.

3.5.5 Additional analysis

In addition to regression model (1), an additional model (3) is applied in order to assess the impact of differences across the sample countries in regulatory quality or sanction severity on target price optimism[50]:

$$\begin{aligned} TPO_{i,j,t} = {} & \beta_0 + \beta_1\, MAD + \beta_2\, RegAttribute + \beta_3\, Affiliation + \beta_4\, MAD \times RegAttribute \\ & + \beta_5\, MAD \times Affiliation + \beta_6\, RegAttribute \times Affiliation + \beta_7\, MAD \times RegAttribute \times Affiliation + \sum \beta_j\, Controls_j \\ & + \sum \beta_j\, Fixed\ Effects_j + \varepsilon \qquad (3) \end{aligned}$$

Thus, the indicator variable *MAD× RegAttribute×Affiliation*, captures the impact of differences in sanction severity and regulatory characteristics between the sample countries on target price optimism of treated broker firms in the post-treatment period. For the definition of the variables, see Table 3.1 and Table 3.2. Here, the indicator variable *RegAttribute* creates two distinct groups in the post-MAD period: One group for countries with high sanction severity or high regulatory quality and a second group for the remaining countries. Several rele-

[50] I use a model with interaction-terms in order to measure incremental effects of different regulatory attributes. See Christensen et al. (2013a) and Barth and Israeli (2013) for more details concerning models with interaction-terms and total-effects models.

vant proxies for sanctions severity and regulatory quality are included, see Table 3.1 and Table 3.2 for details. The results of regression model (3) are reported in Table 3.13. The main effect (indicator *RegAttribute*) was dropped in the regressions, since it was absorbed by country-fixed effects in all regression specifications.

The relevant interaction terms ($MAD \times RegAttribute \times Affiliation$) remain insignificant in all regression models. Thus, the different regulatory attributes do not have a significant impact on target price optimism. This implies that the "*avoidance strategy*" (Leuz and Wysocki 2016, p. 536) applied by financial analysts does not seem to be amplified by more severe sanctions or regulatory quality.

Table 3. 13: Target Price Optimism (TPO) Regressions: Regulatory Attributes

	(1)	(2)	(3)	(4)
Sample Period	2003-2007	2003-2007	2003-2007	2003-2007
RegAttribute	REG_Q	SANC_SEV	S_POWER	PRE_MAD
AFFIL	0.001	-0.036**	-0.002	0.002
	(0.08)	(-2.02)	(-0.13)	(0.14)
MAD	0.009*	0.009	0.009*	-0.000
	(1.92)	(1.16)	(1.94)	(-0.01)
MADxAFFIL	0.023**	0.052**	0.020	0.021
	(2.07)	(2.61)	(1.38)	(1.05)
MADxRegAttribute	-0.002	0.000	-0.002	0.008
	(-0.18)	(0.00)	(-0.22)	(0.91)
MADxRegAttribute xAFFIL	0.006	-0.039	0.009	0.003
	(0.29)	(-1.13)	(0.31)	(0.13)
RegAttribute xAFFIL	-0.003	0.051*	0.002	-0.004
	(-0.13)	(1.68)	(0.09)	(-0.17)
Fixed-Effects-Structure	Broker/Year/ Country/ Industry	Broker/Year/ Country/ Industry	Broker/Year/ Country/ Industry	Broker/Year/ Country/ Industry
Controls	yes	yes	yes	yes
Observations	100719	100719	100719	92658
R^2	0.051	0.052	0.051	0.052
Adjusted R^2	0.050	0.050	0.050	0.050

Notes: The relevant regression model is:

$$TPO = \beta_0 + \beta_1 MAD + \beta_2 RegAttribute + \beta_3 Affiliation + \beta_4 MAD \times RegAttribute + \beta_5 MAD \times Affiliation + \beta_6 RegAttribute \times Affiliation + \beta_7 MAD \times RegAttribute \times Affiliation + \sum \beta_j Controls_j + \sum \beta_j Fixed\ Effects_j + \varepsilon$$

The indicator variable *RegAttribute* creates two distinct groups in the post-MAD period: One group for countries with high values of the respective regulatory characteristic and a second group for the remaining countries. Several relevant proxies for sanctions severity and regulatory quality are included, see Table 3.1 and Table 3.2 for details. Thus, the indicator variable *MAD × RegAttribute × Affiliation*, captures the impact of differences in sanction severity and regulatory characteristics between the sample countries on target price optimism of treated broker firms in the post-treatment period. For the definition of the variables, see Table 3. 2. The regression models include relevant controls (CER S_PERF M_PERF LOG_BSIZE LOG_COV TP_REV LOG_MCAP LOG_MB S_VOL), broker-, country-, industry- and year-fixed effects, if indicated. Standard errors are clustered at the broker-level. The reported values are the coefficients (and t-values in brackets). ***, ** and * indicate significance (two-tailed) at the 1%, 5% and 10% level.

3.6 Conclusion

This paper investigates how EU-regulatory measures influenced the adverse effects of conflicts of interest in financial analysts' investment research. For a sample of firms listed in 13 countries within the European Union, I investigate the impacts of two recent EU-directives, the MAD (Market Abuse Directive) and the MiFID (Markets in Financial Instruments Directive) on financial analysts' target prices and stock recommendations. A recent study by Dubois et al. (2014) concentrates on the effects of the MAD on stock recommendations. I can replicate the results of Dubois et al. (2014) and can provide evidence that the MAD had a mitigating impact on over-optimism in affiliated analysts' stock recommendations. Concerning optimism in target prices, I find a highly significant positive impact of MAD and MiFID on the target price optimism of affiliated financial analysts. Moreover, I cannot find a reduced informativeness of affiliated target price revisions in the post-regulation period, which implies that market participants do not discount target price revisions properly. Since the disclosure requirements of the MAD are geared more explicitly towards stock recommendations, it is less risky for analysts to bias their target prices instead of stock recommendations after the introduction of the MAD. Thus, I interpret my results as an indication of an "*avoidance strategy*" (Leuz and Wysocki 2016, p. 536) applied by financial analysts, who have an economic incentive to bias their research outputs even in the post-regulation period.

4. The Impact of the MAD on Expectations Management[51]

4.1 Introduction

This paper investigates whether the Market Abuse Directive (MAD), which bans selective disclosures, influences firm managements' guidance of analysts' earnings forecasts for a sample of firms listed in 13 EU member countries.

This interaction between analysts and firm management is known as "*forecast guidance*" or "*expectations management*" in the literature (e.g., Matsumoto 2002; Cotter et al. 2006). A typical feature of "*forecast guidance*" is that "*analysts first issue optimistic earnings forecasts and then 'walk down' their estimates to a level that firms can beat at the official earnings announcement*" (Richardson et al. 2004, p.885). Typically, analysts are interested in good relations with a firm's management (e.g., Bradshaw 2011, p. 26) , that is why they pay attention to maintaining their earnings forecasts on a moderate level shortly before the earnings announcement date because the management has an incentive "*to meet or beat*" financial analysts' earnings forecasts (e.g., Degeorge et al. 1999; Bartov et al. 2002, p. 202; Wallmeier 2005), which regularly results in a positive stock price benefit (e.g., Bartov et al. 2002; Das et al. 2011).

Prior literature, mainly from the U.S., provides evidence that firm managers mainly use two instruments - expectations management and earnings management - both of which enable them to reach the profitable earnings benchmarks (Matsumoto 2002; Burgstahler and Eames 2006). More recent studies, e.g. Brown and Pinello (2007) and Das et al. (2011), show a substitutive relation between the two instruments. Thus, firm managers might rely more heavily on forecast guidance when earnings management is more effectively constrained by regulatory measures and vice versa.

[51] I am grateful to the following for their valuable comments: Jörg-Markus Hitz, Nico Lehmann and participants at the Annual Meeting of the European Accounting Association in Tallinn, Estonia (May 2014).

An EU directive, the MAD (Market Abuse Directive, introduced in 2003), addresses market manipulation, insider dealing and the prevention of selective disclosures (e.g., Ferrarini 2004). According to Article 6(3) of the MAD, firms are required to disclose insider information to all market participants and are not allowed to disclose insider information only to selected individual financial analysts (e.g, Avgouleas 2005). Thus, concerning the interaction between firm management and financial analysts, the MAD is comparable to Reg FD, the relevant US regulatory measure regarding the prohibition of selective disclosures (e.g., Ferrarini 2004).

After the introduction of the MAD or Reg FD, private forecast guidance is no longer allowed, thus guidance has to be conducted publicly, which should be a constraint in many cases (Williams and Sun 2011). When the information transfer between firm management and financial analysts becomes more transparent to other market participants, it should be more difficult to achieve a positive stock price benefit by using expectations management (Canace et al., 2010). The results of Wang (2007) show that about half of those US firms in her sample, which relied more heavily on private forecast guidance before the implementation of Reg FD, stopped guidance and did not replace the private forecast guidance with public forecast guidance. Das et al. (2011) and Canace et al. (2010) provide additional evidence and also find a constraining impact of Reg FD on expectations management.

The MAD had to be transposed into national law by EU member countries in order to become applicable (e.g., Enriques and Gatti 2008).[52] A remarkable feature of the MAD is that substantial differences exist across the EU member countries concerning the time of implementation and sanction severity (Christensen et al. 2016). Thus, the European Economic Area represents an ideal setting for the investigation of the impacts of regulatory changes and cross-country differences on the interaction between analysts and firm management.

[52] See MAD, Article 18; Commission Directive 2003/125/EC, Article 10; MiFID, Article 70; Commission Directive 2006/73/EC, Article 53.

In addition to the regulation of selective disclosures, another regulatory step which might influence the prevalence of expectations management was undertaken by several EU member countries in the same period of time. In the years 2001-2009, several countries within the EU introduced, in line with the compulsory introduction of the International Financial Reporting Standards (IFRS), regulatory measures and institutions which are aimed at strengthening the enforcement of accounting standards (Christensen et al. 2013b). These measures can be considered as setting a specific form of legal enforcement, which was investigated as a determinant of expectations management in prior research (e.g., Bonetti 2013; Beccalli et al. 2015). In an empirical investigation, a higher amount of legal enforcement should increase the potential costs of earnings management and thus should increase the prevalence of expectations management (e.g., Bonetti 2013; Beccalli et al. 2015).

Prior studies investigate the impact of different audit requirements between annual and interim reporting on forecast guidance (Brown and Pinello 2007) or the effects of regulatory changes on forecast guidance in a single country setting (e.g., Bartov and Cohen 2009; Das et al. 2011). There are only a rather small number of studies which investigate forecast guidance in a cross-country setting. Brown and Higgins (2005), Bonetti (2013) and Beccalli et al. (2015) investigate the influence of cross-country differences in the amount of legal enforcement or investor protection. Ahmed et al. (2013) and Horton et al. (2013) examine the influence of IFRS adoption on meeting or beating analysts' benchmarks.

Following Matsumoto (2002) and Burgstahler and Eames (2006), I surmise that meeting and beating analysts' forecasts is achieved with the help of two different instruments: expectations management and earnings management. This study concentrates on investigating how the introduction of the MAD influenced the prevalence of expectations management. Thus, I consider the introduction of the MAD and further relevant explanatory variables, such as the introduction of accounting enforcement, as determinants of expectations management.

The identification strategy for measuring the impact of the introduction of the MAD on the prevalence of expectations management utilises the unique features of the European Regulatory setting by exploiting the "*time-series variation*" (Leuz and Wysocki 2016, p. 571) of regulatory changes in the European regulatory environment.

This staggered implementation of the MAD strengthens the empirical approach and should facilitate an accurate identification of the impact of the MAD, since it diminishes the potential impact of confounding regulatory reforms and other confounding market-wide events as well as considerations respective the endogeneity of the timing of the implementation of regulatory reforms (Dubois et al. 2014, p. 502; Christensen et al. 2016).

However, the results provide evidence that the MAD did not have a significant constraining impact on the amount or incidence of expectations management. A strengthened enforcement of accounting does not have an increasing but a significant negative impact on the amount and the incidence of expectations management. Moreover, there is at least some evidence that severe sanctions and extensive competences for regulatory authorities do increase the mitigating impact of the MAD on expectations management.

This study augments prior literature utilising two dimensions. First, by addressing how regulatory changes and cross-country differences could influence the amount of expectations management which is applied by firms, I add to the stream of literature on forecast guidance (e.g., Brown and Pinello 2007; Das et al. 2011). Secondly, I add to the stream of literature that investigates how cross-country differences in enforcement intensity and sanction severity influence the outcome of regulatory reforms (e.g., Christensen et al. 2013b; Dubois et al. 2014; Christensen et al. 2016).

The remainder of this study is organized as follows. Section 4.2 describes the related literature and develops the empirical predictions. Section 4.3 outlines the research design. Section 4.4 presents the sample construction and the empirical findings. The final section is the conclusion.

4.2 Related literature and empirical predictions

Over-optimism of analysts' forecasts could be caused by conflicts of interest to which financial analysts are exposed.[53] There is evidence that analysts try to maintain *"privileged access*" (Carapeto and Gietzmann 2011, p. 757) to managers by pleasing them with overly optimistic forecasts (Bradshaw 2011; Karamanou 2011). Moreover, firm management has an incentive "*to meet or beat*" financial analysts' earnings forecasts (e.g., Degeorge et al. 1999; Bartov et al. 2002, p. 202; Wallmeier 2005), which regularly results in a positive stock price benefit (e.g., Bartov et al. 2002; Das et al. 2011).

In contrast to the abundance of findings for the U.S., only a relatively small number of studies exist for the European market. For example, Daske et al. (2006) provide evidence that meeting and beating earnings benchmarks is quite common among European firms, too. Athanasakou et al. (2009) and Athanasakou et al. (2011) investigate meeting and beating behaviour among British firms. Bonetti (2013) and Beccalli et al. (2015) investigate earnings management and forecast guidance for samples of EU and Swiss firms. Both studies find that cross-country differences in the amount of legal enforcement influence the choice between expectations management and earnings management. Brown and Higgins (2005) provide evidence that forecast guidance is more common in strong-investor-protection countries.

Furthermore, prior studies investigate the impact of different audit requirements between annual and interim reporting on forecast guidance (Brown and Pinello 2007) or the effects of regulatory changes in a single country setting (Bartov and Cohen 2009; Canace et al. 2010; Das et al. 2011). Ahmed et al. (2013) and Horton et al. (2013) examine the influence of the adoption of IFRS on meeting or beating analysts' benchmarks.

[53] E.g., Bradshaw (2011) and Karamanou (2011) categorise different potential sources of conflict. Bradshaw (2011, p. 26) ranks the category "*Currying favor with management*", as the second most important in the relevant literature.

The MAD follows the regulatory approach of the Reg FD, the relevant US-regulatory measure, concerning the prevention of selective disclosures (Ferrarini 2004, p. 733). After the introduction of the MAD or Reg FD, expectations management has to be conducted publicly (Williams and Sun 2011). Expectations management should be constrained by regulatory measures like the Market Abuse Directive (MAD), which prohibits selective disclosures. As Canace et al. (2010, p. 408) point out: the "*Reg FD should significantly reduce expectations management by removing analyst privilege and making communications between management and analysts more public. As communications became more public, expectations management became more transparent to investors, thus reducing its advantages (i.e., positive market reaction).*"

Wang (2007) provides evidence of a "*chilling effect*" of Reg FD, since about half of the firms in her sample stopped guidance and did not replace private forecast guidance with public forecast guidance after the introduction of Reg FD. Thus, the MAD, like the comparable Reg FD, should have the same impact on the interaction between financial analysts and firm management (Avgouleas 2005). When information transfer becomes more transparent to other market participants, referring to (Canace et al., 2010), it should be more difficult to achieve a positive stock price benefit by using expectations management.

Thus, I expect a negative association between the introduction of the MAD and the prevalence of expectations management applied by firms in the post-regulation period. (Prediction I)

Moreover, Dubois et al. (2014) and Christensen et al. (2016) provide evidence on the role of enforcement rigidity and sanction severity on the outcome of regulatory reforms. Both studies find a larger effect of the MAD in countries with stricter enforcement and more severe sanctions. This should also have an impact in the field of the prevention of selective disclosures. When firms are threatened with high sanctions, the firm management should be even more reluctant to risk violations of the rules introduced with the MAD.

Thus, I expect the constraining impact of the MAD on expectations management to be stronger in those EU member countries, which impose stricter sanction on infringements against the provisions of the MAD (Prediction II).

4.3 Research design

4.3.1 Identification strategy and econometric model

The identification strategy for measuring the impact of the introduction of the MAD on the prevalence of expectations management exploits the unique features of the European Regulatory setting. This staggered implementation of the MAD strengthens the empirical approach and should facilitate an accurate identification of the impact of the MAD, since it diminishes the potential impact of confounding regulatory reforms and other confounding market-wide events as well as considerations respective the endogeneity of the timing of the implementation of regulatory reforms (Dubois et al. 2014, p. 502). Thus, the identification strategy exploits the "*time-series variation*" (Leuz and Wysocki 2016, p. 571) of regulatory changes in the European regulatory environment (Leuz and Wysocki 2016, p. 571).

In order to test my empirical *Prediction I*, model 1 is specified. The dependent variable (*EXPM*) in model 1 is either "*magnitude of walk down*" (*MDOWN* - applying an OLS regression) or "*incidence of walk down"* (*IDOWN* - applying a probit regression). *MDOWN*, the approach of Das et al. (2011) and Brown and Pinello (2007), the first metric used as a dependent variable is defined as the difference between the first mean one year consensus forecast, issued one week after the previous annual earnings announcement, and the last mean consensus forecast one day before the current year's annual earnings announcement. A positive value of *MDOW*N indicates forecast guidance, thus MDOWN can be interpreted as the amount of forecast *"walk down*" (Das et al. 2011, p. 1941). MDOWN is scaled with the absolute value of actual earnings per share of the same fiscal year in order to account for currency differences.

A second well established metric, used to capture forecast guidance, is the approach introduced by Bartov et al. (2002), which I define as IDOWN "*incidence of walk down*": an indicator variable that takes the value of one, (1) if actual earnings of a firm are greater than, or equal to, the last mean one year consensus forecast and (2) if actual earnings of a firm are smaller than the first mean one year consensus forecast and zero otherwise. This definition follows the *"incidence of walk down*" specification of Brown and Higgins (2005). The date of the last forecast before the year's annual earnings announcement of a firm is that which is specified as the date of both annual "*walk down"* metrics.

Model 2 is used to test my empirical *Prediction II*. The indicator variable *SANCTION* creates two distinct groups in the post-MAD period: one group for countries with high sanction severity or supervisory power and a second group for the remaining countries. Thus, the indicator variable *MAD× SANCTION* captures the impact of differences in sanction severity and supervisory power between the sample countries in the post-treatment period.

$$EXPM = \beta_0 + \beta_1\, MAD + \sum \beta_j\, Controls_j + \sum \beta_j\, Fixed\ Effects_j + \varepsilon \qquad (1)$$

$$\begin{aligned} EXPM = {} & \beta_0 + \beta_1\, MAD + \beta_2\, SANCTION + \beta_3\, MAD \times SANCTION + \\ & \sum \beta_j\, Controls_j + \sum \beta_j\, Fixed\ Effects_j + \varepsilon \qquad (2) \end{aligned}$$

4.3.2 Measurement of independent variables

MAD is an indicator variable, taking the value of one when a "*walk down"* measure (*WDOWN* or *IDOWN*) is noticed after the Market Abuse Directive was implemented in a country and otherwise zero. *EnfIFRS* is an indicator variable, taking the value of one when a "*walk down"* measure (*WDOWN* or *IDOWN*) is noticed after measures, geared at strengthening the enforcement of IFRS accounting, were implemented in a country and otherwise zero. Information about the accounting-enforcement introduction in EU member states is taken from Christensen et al. (2013b).

The indicator variable *SANCTION* is either *SANC_DISC*, *SANC_SEV* or *S_POWER*. *SANC_DISC* is an indicator variable based on the relevant article MAD Article 6(1), which requires firms to inform the public about insider information.[54] As can be seen in Table 4.1, there are huge cross-country differences concerning sanctions for infringements of MAD Article 6(1). Relevant information about the per country sanction severity for infringements of Article 6(1) of the MAD are taken from the CESR (2008) report and are calculated similar to the sanction severity measures in Christensen et al. (2016). The indicator variable *SANC_DISC* equals one if an unlimited fine or a profit-based fine is possible in a country and zero otherwise.

SANC_SEV is an indicator variable, taking the value of one when the rank of the sanction severity index by Dubois et al. (2014) in a country is below the sample median and otherwise zero. The sample countries "*are ranked based on their respective administrative pecuniary penalties, criminal sanctions, and fines ([MAD] articles 4, 6.3, 6.5, and 14.3). For each country, the average rank for the three sorts of sanctions is the sanction severity index* " (Dubois et al. 2014, p. 525). Countries are ranked from 1 (highest sanction severity) to 12 (lowest sanction severity). The calculation of this indicator Dubois et al. (2014).

[54] I choose MAD Article 6(1), the more restrictive main rule, which means that there might be some cases in which a disclosure would be required according to MAD Article 6(3) but not according to MAD Article 6(1) (Lau Hansen and Moalem 2009, p. 335, 339).

S_POWER, is an indicator variable, taking the value of one, when the count of positive answers (to a questionnaire answered by European regulators about their competences in the case of MAD) is above the sample median and zero otherwise. Relevant information for this indicator variable is obtained from (Christensen et al. 2016). The calculation of this indicator follows Christensen et al. (2016).

The indicator variables of my regression models are added to a comprehensive set of control variables at the firm-level and thus follows relevant literature. (e.g., Brown and Higgins 2005; Brown and Pinello 2007; Das et al. 2011; Gupta et al. 2013). My fixed effects structure includes industry-, year- and country-fixed effects and also follows relevant prior literature (e.g., Brown and Higgins 2005; Brown and Pinello 2007; Das et al. 2011; Gupta et al. 2013).

I include the variables natural log of market capitalisation (*LN_MCAP*)[55], an indicator variable loss, which equals one if a company experienced a loss in a fiscal year and zero otherwise, the variables natural log of the market to book ratio (*LN_MB*) and the absolute forecast error (*FE_ABS*), which is calculated as the absolute value of the difference between actual earnings per share in a fiscal year and the first mean one year consensus forecast which is issued one week after the previous annual earnings announcement. Furthermore, the natural logarithm of one plus the number of analysts (LN_COV) covering a firm at the date of the last forecast before the year's annual earnings announcement is included. The number of analysts is the number of estimates included in the I/B/E/S consensus recommendation for a firm.

Moreover, I follow the approach of Dubois et al. (2014), who consider the country of a firm`s primary listing as the relevant jurisdiction in the case of the MAD and exclude firms, which are not incorporated and not primarily listed in the same country, in order to assure the determination of relevant jurisdiction in case of cross border activities. Detailed information concerning the construction of the variables can be obtained from Table 4.2.

[55] Measured in EURO.

Table 4. 1: Implementation Strength and Entry-into-Force-Dates

	Implementation Strength						Entry-into-Force Dates	
Country	MAD sanction severity Art 6.(1)		Sanction severity		Supervisory Power		MAD	Accounting Enforcement
	Max Fine by Regulator	Indicator Variable	Index value	Indicator Variable	Index value	Indicator Variable		
Austria	€ 30,000	0	10	0	70	0	1-Jan-2005	No
Belgium	€ 2,500,000 or 3 times the Profit	1	4	1	69	0	19-Sep-2005	No
Denmark	No	0	12	0	60	0	1-Apr-2005	No
Finland	200,000	0	12	0	63	0	1-Jul-2005	Yes (2005 Q1)
France	€ 1,500,000	0	4	1	75	1	27-Jul-2005	No
Germany	€ 1,000,000	0	9	0	64	0	30-Oct-2004	Yes (2005 Q4)
Ireland	€ 2,500,000 + Costs of Regulator	0	4	1	73	1	6-Jul-2005	Yes (2007 Q3)
Italy	€ 500,000	0	2	1	70	0	18-May-2005	No
The Netherlands	€ 96,000	0	7	0	67	0	1-Oct-2005	Yes (2005 Q4)
Portugal	€ 2,500,000	0	7	0	73	1	15-Apr-2006	No
Spain	5 times the Profit	1	2	1	60	0	24-Nov-2005	No
Sweden	Amount not available	n.a.	11	0	73	1	1-Jul-2005	Yes (2007 Q3)
United Kingdom	Unlimited fines	1	1	1	76	1	1-Jul-2005	Yes (2005 Q2)

Table 4.1 provides information about implementation strength meausures and entry-into-force-dates. The per country sanction severity for infringments of Article 6(1) of the MAD are taken from the CESR (2008) report and are calculated similar as in Christensen et al. (2016): the indicator variable equals one if a unlimited fine or a profit-based fine is possible in a country and zero otherwise. Table 4.2 contains more details concerning the sanction severity and supervisory power measures. Entry-into-force dates of the MAD were obtained from the European Commission website, Accounting Enforcment entry-into-force dates are taken from Christensen et al. (2013b).

Table 4. 2: Definition of Variables

Variable		Definition	Data sources
Dependent Variable			
Magnitude of Walk Down	MDOWN	The difference between the first mean one year consensus forecast, issued one week after the previous annual earnings announcement, and the last mean consensus forecast one day before the current year's annual earnings announcement. Definition follows Das et al. (2011) and Brown and Pinello (2007). MDOWN is scaled with the absolute value of actual earnings per share of the same fiscal year in order to account for currency differences and calculated on the date of the last forecast before the current year's annual earnings announcement.	I/B/E/S Consensus
Incidence of Walk Down	IDOWN	Indicator variable that takes the value of one, (1) if actual earnings of a firm are greater than, or equal to, the last mean one year consensus forecast and (2) if actual earnings of a firm are smaller than the first mean one year consensus forecast and zero otherwise. This definition follows the "*incidence of walk down*" specification of Brown and Higgins (2005). IDOWN is calculated on the date of the last forecast before the current year's annual earnings announcement.	I/B/E/S Consensus
Independent Variables: Regulation related			
Reg_Indicator_ 1: Market Abuse Directive	MAD	Indicator variable, taking the value of one when a "*walk down*" measure (MDOWN or IDOWN) is noticed after the Market Abuse Directive was implemented in a country and otherwise zero.	European Commission
Sanction Severity of MAD	SANC_SEV	Indicator variable, taking the value of one when the rank of the sanction severity index by Dubois et al. (2014) in country c is below the sample median and otherwise zero. The sample countries "*are ranked based on their respective administrative pecuniary penalties, criminal sanctions, and fines ([MAD] articles 4, 6.3, 6.5, and 14.3). For each country, the average rank for the three sorts of sanctions is the sanction severity index*" Dubois et al. (2014, p.525). Countries are ranked from 1 (highest sanction severity) to 12 (lowest sanction severity).	Dubois et al. (2014)

(Table 4.2 continued)

Supervisory Power	S_POWER	Indicator variable, taking the value of one, when the count of positive answers (in a questionnaire answered by European regulators concerning their competences in case of MAD) is above the sample median and zero otherwise.	Christensen et al. (2016)
Sanction for Infringements of Art. 6(1) MAD	SANC_DISC	Indicator variable based on the relevant Article 6 (1) of the MAD, which requires firms to inform the public about insider information. Relevant information about the per country sanction severity for infringements of Article 6(1) of the MAD are taken from the CESR (2008) report and are calculated as similar to the sanction severity measures in Christensen et al. (2016). The indicator variable *SANC_DISC* equals one if an unlimited fine or a profit-based fine is possible in a country and otherwise zero.	CESR (2008)
Independent variables: Control variables			
Introduction of IFRS Enforcement	EnfIFRS	Indicator variable, taking the value of one when a "*walk down*" measure (MDOWN or IDOWN) is noticed after measures, which were geared at strengthening the enforcement of IFRS, were implemented in a country and otherwise zero. Information about the accounting-enforcement introduction in EU member states is taken from Christensen et al. (2013b).	Christensen et al. (2013b)
Market capitalisation	LN_MCAP	The natural logarithm of market capitalization (in Million Euro) of a firm on the date of the last forecast before the current year's annual earnings announcement of the firm.	Datastream
Market-to-Book Ratio	LN_MB	The natural logarithm of the Market-to-Book Ratio of a firm on the date of the last forecast before the current year's annual earnings announcement of the firm.	Datastream
Incidence of a loss in the fiscal year	LOSS	Indicator variable, which equals one if a firm experienced a loss in a fiscal year and zero otherwise.	I/B/E/S Consensus

(Table 4.2 continued)

Coverage intensity	LN_COV	The natural logarithm of one plus the number of analysts covering a firm on the date of the last forecast before the current year's annual earnings announcement of the firm. Number of analysts is the number of estimates included in the I/B/E/S consensus recommendation for the firm.	I/B/E/S Consensus
Absolute Forecast Error	FE_ABS	Absolute value of the difference between actual earnings per share in a fiscal year and the first mean one year consensus forecast which is issued one week after the previous annual earnings announcement. FE_ABS is scaled with the absolute value of actual earnings per share of the same fiscal year in order to account for currency differences.	I/B/E/S Consensus
Industry indicator	IBSCT	Industry indicators are based on the I/B/E/S industry sector classification (IBSCT).	I/B/E/S
Fixed effects structure: industry-, year- and country-fixed effects; standard errors clustered at the firm-level.			I/B/E/S; Datastream; Worldscope

4.4 Results

4.4.1 Sample construction and descriptive statistics

I examine a sample of I/B/E/S analyst earnings per share (EPS) consensus forecasts for firms listed in 13 countries within the EU for the sample period 2000-2009. In order to enable the utilization of the sanction severity index from Dubois et al. (2014), I restrict my sample to the same countries as in their study. The sample period was chosen in order to align the sample with the study of Christensen et al. (2013b), where the information concerning the introduction of accounting enforcement measures was obtained from.

I start with all firms listed in the Worldscope country-lists of these 13 countries. The sample was reduced due to missing data in I/B/E/S and Worldscope. Altogether I could obtain 24265 firm-year observations within the years 2000 to 2009 from 13 countries. The sample size was further reduced in the regression specifications due to missing data. Analyst earnings per share mean forecast data was taken from the I/B/E/S consensus database, further data concerning market capitalisation, market to book ratio, actual earnings, annual earnings announcement days and industry-sectors was obtained from Datastream, Worldscope and I/B/E/S. Information concerning sanction severity, the IFRS enforcement indicator and the MAD indicator was obtained from CESR (CESR 2008), Christensen et al. (2013b), Dubois et al. (2014), Christensen et al. (2016) and the website of the European Commission. Moreover, the dependent variable MDOWN was winsorized (at the 1st and 99th percentile).

Table 4.3 provides descriptive statistics, and correlations of continuous and indicator variables based on the full sample. Table 4.4 provides further details concerning the sample composition and the distribution of firm-year observations sorted by country and year.

Table 4. 3: Descriptive Statistics

Table 4. 3, Panel A

	mean	min	p25	p50	p75	max
MDOWN	0.524	-1.429	-0.061	0.049	0.412	12.609
IDOWN	0.192	0.000	0.000	0.000	0.000	1.000
MAD	0.547	0.000	0.000	1.000	1.000	1.000
EnfIFRS	0.328	0.000	0.000	0.000	1.000	1.000
LN_COV	1.811	0.693	1.099	1.792	2.485	4.007
LN_MCAP	5.753	-1.772	4.265	5.587	7.089	12.533
LOSS	0.165	0.000	0.000	0.000	0.000	1.000
FE_ABS	3.188	0.000	0.097	0.266	0.819	25001.000
LN_MB	0.589	-4.605	0.068	0.548	1.044	8.349

Table 4. 3, Panel B

	MDOWN	IDOWN	EnfIFRS	MAD	LN_COV	LN_MCAP	LN_MB	LOSS	FE_ABS
MDOWN	1.00								
IDOWN	0.17^{***}	1.00							
EnfIFRS	0.00	0.02^{**}	1.00						
MAD	-0.00	0.00	0.64^{***}	1.00					
LN_COV	-0.08^{***}	0.02^{**}	-0.09^{***}	-0.06^{***}	1.00				
LN_MCAP	-0.15^{***}	-0.02^{***}	-0.12^{***}	-0.01	0.81^{***}	1.00			
LN_MB	-0.11^{***}	-0.05^{***}	-0.01	-0.02^{**}	0.13^{***}	0.24^{***}	1.00		
LOSS	0.19^{***}	-0.04^{***}	0.02^{**}	-0.01	-0.21^{***}	-0.32^{***}	-0.04^{***}	1.00	
FE_ABS	0.04^{***}	-0.00	-0.01	-0.01	-0.01	-0.02^{**}	0.01	0.02^{**}	1.00

Table 4.3, Panel A shows the descriptive statistics for continuous and indicator variables in the baseline regressions (Tables 4.5 and 4.6). Variables are defined in Table 4.2. Table 4.3, Panel B shows the Pearson's correlation coefficients for variables included in the baseline regressions (Tables 4.5 and 4.6). The reported values are the coefficients (and t-values in brackets). ***, ** and * indicate significance (two-tailed) at the 1%, 5% and 10% level.

Table 4. 4: Sample Composition - Firm-Years sorted by Country and Year

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	Total
Austria	39	29	32	25	28	33	42	45	49	43	365
Belgium	70	54	53	68	76	84	83	94	90	81	753
Denmark	77	56	55	56	75	73	79	83	72	72	698
Finland	95	97	93	92	92	100	103	105	97	88	962
France	282	238	244	301	297	343	377	399	381	353	3215
Germany	366	319	303	265	280	318	346	411	374	404	3386
Ireland	39	37	35	34	31	31	34	37	33	32	343
Italy	130	139	129	141	161	174	188	202	165	171	1600
Netherlands	142	119	115	109	109	105	105	104	94	90	1092
Portugal	31	27	28	24	27	30	26	32	31	31	287
Spain	101	88	83	90	101	100	100	109	105	104	981
Sweden	173	136	140	134	132	144	165	184	171	191	1570
United Kingdom	816	762	813	786	848	924	1026	1038	1014	986	9013
Total	2361	2101	2123	2125	2257	2459	2674	2843	2676	2646	24265

Table 4.4 shows the number of Firm-Years contained in the sample, sorted by country and year

4.4.2 Empirical findings

Table 4.5 reports the results of the regression investigating the impact of the MAD on the amount of expectations management (MAD - Baseline - MDOWN) with different regression specifications (models 1-4). Models 1 and 2 are estimates based on the full sample. In models 3 and 4 firms with their main-listing in the United Kingdom are excluded from the sample. This exclusion is done for two reasons. First of all, the firms listed in the United Kingdom form the largest group in the sample and thus could dominate the results. Secondly, private forecast guidance is common in the UK, even in the post-regulation period, according to Athanasakou et al. (2011, p. 62). In Table 4.5 it becomes obvious that the MAD indicator, the variable of interest, remains insignificant in all four regression specifications. In regression models 2 and 4, *EnfIFRS* is included as an additional control. It is of interest that the introduction of accounting enforcement does not have an increasing but a reducing impact (significant at the 5%-level in model 2 and at the 10%-level in model 4). The other control variables, except *FE_ABS*, are highly significant in all four regression specifications.

Table 4.6 reports the results of the regression investigating the impact of the MAD on the incidence of expectations management (MAD - Baseline - IDOWN) with different regression specifications (models 1- 4). The results show a similar picture when compared with Table 4.5. Also in the case of the *IDOWN*-indicator, the MAD does not have a significant impact. In model 2, *EnfIFRS* has only a weakly significant impact on *IDOWN*. The remaining control variables, except *FE_ABS*, are highly significant in all four regression specifications.

Table 4.7 reports the results of the regression investigating the impact of differences in sanction severity and supervisory powers between the sample countries on the amount of forecast walk down (MDOWN) using different regression specifications (models 1-6). The main effect (indicator *SANCTION*) was dropped in the regressions, since it was absorbed by country-fixed effects in all regression specifications. While the MAD indicator by itself does not have a significant impact, the interaction terms *MAD×S_POWER* in model 2 (significant at the 10%-level) and model 5 (significant at the 5%-level) and *MAD×SANC_SEV* in model 6 (significant at 10%-level) have their predicted negative sign and have a significant impact on MDOWN. *EnfIFRS* has a negative sign and a significant impact on MDOWN in all six models. Again, other control variables, except *FE_ABS*, are highly significant in all six regression specifications.

Table 4. 5: MAD – Baseline – MDOWN

	(1) Full Sample	(2) Full Sample	(3) UK excluded	(4) UK excluded
MAD	-0.024 (-0.29)	0.001 (0.02)	0.054 (0.43)	0.026 (0.21)
EnfIFRS		-0.101** (-2.33)		-0.104* (-1.82)
LN_COV	0.173*** (6.99)	0.177*** (7.13)	0.183*** (6.28)	0.185*** (6.35)
LN_MCAP	-0.131*** (-11.14)	-0.133*** (-11.28)	-0.140*** (-9.84)	-0.141*** (-9.89)
LN_MB	-0.130*** (-7.33)	-0.128*** (-7.26)	-0.151*** (-6.62)	-0.149*** (-6.57)
LOSS	0.725*** (14.59)	0.724*** (14.56)	0.745*** (12.24)	0.742*** (12.16)
FE_ABS	0.000 (0.94)	0.000 (0.93)	0.006** (2.50)	0.006** (2.49)
Fixed-Effects	yes	yes	yes	yes
Observations	22438	22438	14404	14404
R^2	0.067	0.067	0.102	0.102
Adjusted R^2	0.065	0.065	0.099	0.100

Notes: The relevant regression in models (1) - (4) is:

$MDOWN = \beta_0 + \beta_1 MAD + \sum \beta_j Controls_j + \sum \beta_j Fixed\ Effects_j + \varepsilon$

The indicator variable MAD measures the impact of the introduction of the MAD on the magnitude of forecast walk down (MDOWN). In model 3-4, firms with primary listing in the United Kingdom are excluded from the sample. For the definition of the variables, see Table 4.2. The regression models include country-, industry- and year-fixed effects. Standard errors are clustered at the firm-level. The reported values are the coefficients (and t-values in brackets). ***, ** and * indicate significance (two-tailed) at the 1%, 5% and 10% level.

Table 4. 6: MAD – Baseline – IDOWN

	(1) Full Sample	(2) Full Sample	(3) UK excluded	(4) UK excluded
MAD	-0.107	-0.086	-0.055	-0.066
	(-1.54)	(-1.23)	(-0.58)	(-0.69)
EnfIFRS		-0.069*		-0.042
		(-1.80)		(-0.88)
LN_COV	0.136***	0.138***	0.136***	0.137***
	(6.20)	(6.30)	(5.17)	(5.20)
LN_MCAP	-0.054***	-0.055***	-0.071***	-0.071***
	(-5.24)	(-5.34)	(-5.39)	(-5.42)
LN_MB	-0.069***	-0.068***	-0.070***	-0.069***
	(-4.68)	(-4.61)	(-3.61)	(-3.58)
LOSS	-0.245***	-0.246***	-0.284***	-0.285***
	(-7.99)	(-8.02)	(-7.28)	(-7.31)
FE_ABS	0.000	0.000	0.000*	0.000*
	(0.32)	(0.30)	(1.95)	(1.95)
Fixed-Effects	yes	yes	yes	yes
Observations	22438	22438	14404	14404
Pseudo R^2	0.026	0.026	0.036	0.036

Notes: The relevant regression in models (1) - (4) is:

$IDOWN = \beta_0 + \beta_1 MAD + \sum \beta_j \, Controls_j + \sum \beta_j \, Fixed\ Effects_j + \varepsilon$

The indicator variable MAD measures the impact of the introduction of the MAD on the incidence of forecast walk down (IDOWN). In model 3-4, firms with primary listing in the United Kingdom are excluded from the sample. For the definition of the variables, see Table 4.2. The regression models include country-, industry- and year-fixed effects. Standard errors are clustered at the firm-level. The reported values are the coefficients (and t-values in brackets). ***, ** and * indicate significance (two-tailed) at the 1%, 5% and 10% level.

Table 4.8 reports the results of the regression investigating the impact of differences in sanction severity and supervisory powers between the sample countries on the incidence of forecast walk down (*IDOWN*) using different regression specifications (models 1-6). The main effect (indicator *SANCTION*) was dropped in the regressions, since it was absorbed by country-fixed effects in all regression specifications. In this case, neither MAD nor the interaction terms have a significant impact on *IDOWN*. *EnfIFRS* is only weakly significant in one case, having a negative sign in model 2. Also in this case, the other control variables, except *FE_ABS*, are highly significant in all six regression specifications.

The overall results show that the MAD did not have a significant impact on expectations management. Thus the findings are not in line with empirical *Prediction I*. Thus, my results differ from the findings of Das et al. (2011), who find a significant reducing impact of the Reg FD on expectations management.

However, *EnfIFRS* seems to have a significant negative impact on the amount and the incidence of expectations management. However, one would expect that strengthened enforcement of accounting should have a constraining influence on earnings management. Thus, more managers might concentrate on expectations management. However, the regression results do not suggest such a substitutive relationship between strengthened enforcement of accounting and expectations management. Thus my results are in contrast to the findings of Bonetti (2013) and Beccalli et al. (2015), who investigate earnings management and forecast guidance for samples of EU and Swiss firms. Both studies find that the amount of legal enforcement is positively associated with expectations management. However, neither study investigates a regulatory change but pure country-level differences ("*cross-sectional variation*" (Leuz and Wysocki 2016, p. 571)). Moreover, there is at least some evidence, that severe sanctions and extensive competences for regulatory authorities increase the mitigating impact of the MAD on expectations management, which is in line with empirical *Prediction II*.

Table 4. 7: MAD – Sanction Severity – MDOWN

	(1)	(2)	(3)	(4)	(5)	(6)
Sample	Full Sample	Full Sample	Full Sample	UK excluded	UK excluded	UK excluded
SANCTION	SANC_DISC	S_POWER	SANC_SEV	SANC_DISC	S_POWER	SANC_SEV
MAD	0.010	0.049	0.036	0.017	0.062	0.058
	(0.11)	(0.55)	(0.39)	(0.13)	(0.49)	(0.46)
MADxSANCTION	-0.029	-0.086*	-0.053	0.006	-0.130**	-0.135*
	(-0.53)	(-1.75)	(-1.02)	(0.07)	(-2.08)	(-1.71)
EnfIFRS	-0.091*	-0.087**	-0.108**	-0.083	-0.135**	-0.188**
	(-1.69)	(-1.96)	(-2.47)	(-1.22)	(-2.24)	(-2.44)
LN_COV	0.172***	0.177***	0.177***	0.181***	0.183***	0.185***
	(6.82)	(7.14)	(7.16)	(6.03)	(6.29)	(6.34)
LN_MCAP	-0.131***	-0.133***	-0.133***	-0.138***	-0.141***	-0.141***
	(-10.94)	(-11.32)	(-11.33)	(-9.39)	(-9.88)	(-9.91)
LN_MB	-0.131***	-0.128***	-0.128***	-0.158***	-0.150***	-0.151***
	(-7.06)	(-7.27)	(-7.27)	(-6.36)	(-6.63)	(-6.64)
LOSS	0.712***	0.724***	0.725***	0.739***	0.740***	0.743***
	(13.79)	(14.57)	(14.56)	(11.46)	(12.13)	(12.18)
FE_ABS	0.000	0.000	0.000	0.006**	0.006**	0.006**
	(0.90)	(0.93)	(0.93)	(2.05)	(2.49)	(2.49)
Fixed-Effects	yes	yes	yes	yes	yes	yes
Observations	20969	22438	22438	12935	14404	14404
R^2	0.065	0.067	0.067	0.096	0.102	0.102
Adjusted R^2	0.063	0.065	0.065	0.093	0.100	0.100

(continued)

(Table 4.7 continued)

Notes: The relevant regression in models (1) - (4) is:

$MDOWN = \beta_0 + \beta_1 MAD + \beta_2 SANCTION + \beta_3 MAD \times SANCTION + \sum \beta_j Controls_j + \sum \beta_j Fixed\ Effects_j + \varepsilon$

The indicator variable *MAD* measures the impact of the introduction of the MAD on the magnitude of forecast walk down (*MDOWN*). The indicator variable *SANCTION* creates two distinct groups in the post-MAD period: One group for countries with high sanction severity or supervisory powers and a second group for the remaining countries. See Table 4.1 and Table 4.2 for details concerning the regulatory attributes *SANC_DISC*, *S_POWER*, *SANC_SEV* applied. The indicator variable *MAD* × *SANCTION* captures the impact of differences in sanction severity and supervisory powers between the sample countries on forecast walk down (*MDOWN*). In models 4-6, firms with primary listing in the United Kingdom are excluded from the sample. For the definition of the variables, see Table 4.2. The regression models include country-, industry- and year-fixed effects. Standard errors are clustered at the firm-level. The reported values are the coefficients (and t-values in brackets). ***, ** and * indicate significance (two-tailed) at the 1%, 5% and 10% level.

Table 4. 8: MAD – Sanction Severity – IDOWN

	(1)	(2)	(3)	(4)	(5)	(6)
Sample	Full Sample	Full Sample	Full Sample	UK excluded	UK excluded	UK excluded
SANCTION	SANC_DISC	S_POWER	SANC_SEV	SANC_DISC	S_POWER	SANC_SEV
MAD	-0.075	-0.087	-0.078	-0.098	-0.090	-0.092
	(-1.04)	(-1.19)	(-1.03)	(-1.00)	(-0.93)	(-0.94)
MADxSANCTION	-0.037	0.002	-0.012	0.052	0.085	0.114
	(-0.83)	(0.05)	(-0.27)	(0.64)	(1.57)	(1.60)
EnfIFRS	-0.073*	-0.069*	-0.070*	-0.052	-0.019	0.031
	(-1.67)	(-1.79)	(-1.81)	(-0.95)	(-0.37)	(0.46)
LN_COV	0.139***	0.138***	0.138***	0.136***	0.138***	0.137***
	(6.16)	(6.30)	(6.31)	(4.98)	(5.23)	(5.22)
LN_MCAP	-0.055***	-0.055***	-0.055***	-0.072***	-0.071***	-0.071***
	(-5.22)	(-5.34)	(-5.35)	(-5.22)	(-5.42)	(-5.41)
LN_MB	-0.069***	-0.068***	-0.068***	-0.072***	-0.069***	-0.068***
	(-4.45)	(-4.61)	(-4.61)	(-3.42)	(-3.56)	(-3.52)
LOSS	-0.247***	-0.246***	-0.246***	-0.293***	-0.284***	-0.286***
	(-7.81)	(-8.02)	(-8.01)	(-7.14)	(-7.28)	(-7.32)
FE_ABS	-0.000	0.000	0.000	0.000	0.001*	0.000**
	(-0.13)	(0.30)	(0.30)	(1.57)	(1.95)	(2.00)
Fixed-Effects	yes	yes	yes	yes	yes	yes
Observations	20969	22438	22438	12935	14404	14404
Pseudo R^2	0.025	0.026	0.026	0.036	0.036	0.036

(continued)

(Table 4.8 continued)

Notes: The relevant regression in models (1) - (4) is

$$IDOWN = \beta_0 + \beta_1 MAD + \beta_2 SANCTION + \beta_3 MAD \times SANCTION + \sum \beta_j Controls_j + \sum \beta_j Fixed\ Effects_j + \varepsilon$$

The indicator variable *MAD* measures the impact of the introduction of the MAD on the incidence of forecast walk down (*IDOWN*). The indicator variable *SANCTION* creates two distinct groups in the post-MAD period: One group for countries with high sanction severity or supervisory powers and a second group for the remaining countries. See Table 4.1 and Table 4.2 for details concerning the regulatory attributes *SANC_DISC*, *S_POWER*, *SANC_SEV* applied. The indicator variable *MAD × SANCTION* captures the impact of differences in sanction severity and supervisory powers between the sample countries on forecast walk down (*IDOWN*). In models 4-6, firms with primary listing in the United Kingdom are excluded from the sample. For the definition of the variables, see Table 4.2. The regression models include country-, industry- and year-fixed effects. Standard errors are clustered at the firm-level. The reported values are the coefficients (and t-values in brackets). ***, ** and * indicate significance (two-tailed) at the 1%, 5% and 10% level.

4.5 Conclusion

This paper investigates whether recent EU regulatory measures influenced the interaction between analysts and firm management, which is known as "*forecast guidance*" or "*expectations management*" in the literature (e.g., Matsumoto 2002; Cotter et al. 2006). While the study concentrates on investigating how the introduction of the MAD influenced the prevalence of expectations management, there is no overall evidence, that the amount or incidence of expectations management was reduced by the introduction of the prohibition of selective disclosures. However, there is at least some evidence that countries, which introduced severe sanctions for infringements of the MAD and extensive competences for regulatory authorities, experienced a stronger mitigating impact of the MAD on expectations management. The results of this empirical study are subject to the limitations of the recording of expectations management. Expectations management cannot be observed directly, thus several metrics for capturing the amount or incidence of expectations management were introduced in the relevant literature (Beccalli et al. 2015, p. 8). However, a consensus does not exist concerning the advantageousness of the different metrics (Beccalli et al. 2015, p. 8). I applied two well established metrics. However, there are further variants (e.g., Matsumoto 2002; Athanasakou et al. 2011). Moreover, I do not include the approach of Wang (2007), who developed a measure for capturing private earnings guidance.

5. Affiliated Analyst Coverage and SEO Underpricing - The Impact of MAD and MiFID[56]

5.1 Introduction

This study investigates whether the Market Abuse Directive (MAD), which bans selective disclosures (e.g., Ferrarini 2004) as well as the Markets in Financial Instruments Directive (MiFID), which includes organizational requirements ("*chinese walls*") and conduct-of-business rules for investment banks (e.g., Enriques 2006), reduce the effectiveness of coverage by analysts with close links to firms ("*affiliated analysts*") in the context of seasoned equity offerings (SEOs) for a sample of SEOs by firms listed in 13 countries within the European Union.

Prior literature (e.g., Altınkılıç and Hansen 2003; Corwin 2003; Mola and Loughran 2004; Bowen et al. 2008; Huang and Zhang 2011) provides evidence, that SEOs are underpriced, which means that shares in an SEO have to be issued with a discount, which increases the cost of issuing equity capital (e.g., Bowen et al. 2008). This discount can be caused by, among other reasons, information asymmetries among investors and can be reduced by public disclosures of relevant information or by financial analysts covering the issuing firm before the SEO (Bowen et al. 2008). The study by Bowen et al. (2008) finds a significant reducing impact of analyst coverage on the discount in SEOs. SEO underpricing is further reduced in the study of Bowen et al. (2008), when issuing firms are covered by affiliated analysts, who work for the main underwriter of the SEO. These analysts should have "*privileged access*" (Carapeto and Gietzmann 2011, p. 757) to company information due to their employers' involvement in the marketing of the SEO and the due diligence investigations (Michaely and Womack 1999, p. 656; Bradley et al. 2003, p. 3; Bowen et al. 2008, p. 666).

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“*Privileged access*” (Carapeto and Gietzmann 2011, p. 757) to company information for affiliated analysts was addressed by recent regulatory measures in the US and European Union (e.g., Enriques 2006; Lau Hansen and Moalem 2009, p. 334; Koch et al. 2013). In Europe, the MAD (introduced in 2003), addresses market manipulation, insider dealing and the prevention of selective disclosures (e.g., Ferrarini 2004). According to Article 6.3 of the MAD, firms are required to disclose insider information to all market participants and are not allowed to disclose insider information to only selected individual financial analysts, which makes the MAD comparable to Reg FD, the relevant US regulatory measure regarding the prohibition of selective disclosures (Avgouleas 2005, p. 211; Lau Hansen and Moalem 2009, p. 334). After the introduction of the MAD or Reg FD, it should be more difficult for analysts with close links to firms to receive firm information via selective disclosures (e.g., Ferrarini 2004, p. 733; Koch et al. 2013). This is because firm management could become more restrictive in providing information after the prohibition of selective disclosures, when they stop providing selective disclosures to a small privileged group of affiliated financial analysts because they do not want to publicly disclose the information (e.g., Cornett et al. 2007; Canace et al. 2010). Prior research on the effectiveness of Reg FD (e.g., Gintschel and Markov 2004; Mohanram and Sunder 2006; Kim and Jung 2012) suggests, that Reg FD has reduced the informativeness and accuracy of financial analysts with “*privileged access*“ (Carapeto and Gietzmann 2011, p. 757), since superior forecasting performance was based on information obtained from selective disclosures. However, since there are institutional differences between the US and the European regulatory setting, it is an open question as to whether comparable results can be found in the case of the MAD.

The MiFiD and implementing Commission Directive 2006/73/EC include organizational requirements and conduct-of-business rules for investment firms and banks in order to contain possible conflicts of interest in investment research (Enriques 2006). These provisions by the MiFID for investment firms and banks should have an additional constraining impact on a possible "*privileged access*" (Carapeto and Gietzmann 2011, p. 757) to company information for affiliated financial analysts (Enriques 2006).

Taken altogether, the SEO setting is a very specific setting in which the provision of selective disclosures to affiliated financial analysts can be of advantage for firms raising new equity capital, since affiliated coverage can help to reduce SEO underpricing. Thus, the SEO setting facilitates investigating whether the regulatory measures, which are geared up to prevent the transfer of private information from firms to affiliated financial analysts, reduced the effect of affiliated analyst coverage in the context of SEOs.

The MAD had to be transposed into national law by EU member countries in order to become applicable.[57] According to Christensen et al. (2016), a remarkable feature of the MAD is that substantial differences exist across the EU member countries concerning the time of implementation and the severity of the sanctions. Thus, the European Economic Area represents an ideal setting for the investigation of the impacts of regulatory changes and cross-country differences (Christensen et al. 2016).

The identification strategy for measuring the impact of the introduction of the MAD and MiFID on the effectiveness of coverage by affiliated financial analysts in reducing the discounting of seasoned equity offerings (SEOs) applies a Difference-in-Difference (DiD) regression design and exploits, in the case of the MAD, the unique features of the European Regulatory setting.

The results of my empirical analysis provide evidence for a reduced effectiveness of affiliated coverage after the introduction of the MAD and the MiFID, which results in increased SEO underpricing in affected SEOs. Moreover, the findings of my DiD-design are consistent over different control groups (SEOs with no prior analyst coverage and SEOs with pure unaffiliated prior coverage). Thus, after the introduction of the regulatory measures, the competi-

[57] See MAD, Article 18; Commission Directive 2003/125/EC, Article 10; MiFID, Article 70; Commission Directive 2006/73/EC, Article 53.

tive advantage of affiliated analysts vanishes. However, the results are partly driven by new firms, which did not issue equity capital before the year 2008, as shown in one of the robustness tests. Moreover, my results provide evidence that differences in sanction severity and supervisory power concerning the MAD between the sample countries do not have an impact on underpricing of treated SEOs in the post-treatment period. Thus, in this specific setting, my results do not go along the same lines of related studies which investigate the effectiveness of regulatory measures in the European regulatory environment such as Dubois et al. (2014) and Christensen et al. (2016).

I augment the findings in prior literature utilising two dimensions. First, by adding to the SEO underpricing literature (e.g., Corwin 2003; Mola and Loughran 2004; Bowen et al. 2008; Huang and Zhang 2011). This, to my knowledge, is the first study to investigate how regulatory changes influence the impact of analyst coverage on SEO underpricing in an international cross country setting

Bowen et al. (2008) and Huang and Zhang (2011) investigate the impact of analyst coverage for samples of US-SEOs, while Gupta et al. (2013), who examine the impact of regulatory differences on SEO underpricing, do not include analyst coverage as an explanatory variable in their international sample of SEOs from 39 countries. Moreover, the SEO underpricing setting provides, in contrast to indirect measures like bid-ask spreads or estimated discount rates obtained from valuation models, an accurate direct measure for the cost of capital (Bowen et al. 2008, p. 662). In addition to this advantage, SEO underpricing should be less affected by endogeneity issues, since it is measured after the number of covering analysts is determined and over a short time interval of just one day (Bowen et al. 2008, p. 662).

Second, by exploiting the "*time-series variation*" (Leuz and Wysocki 2016, p. 571) of regulatory changes as well as "*cross-sectional variation*" (Leuz and Wysocki 2016, p. 571) in the European regulatory environment, I add to the growing stream of literature (Christensen et al.

2013b; Dubois et al. 2014; Christensen et al. 2016) which investigates the impact of regulatory changes on the basis of the unique European regulatory environment.

The remainder of this paper is organized as follows. Section 5.2 discusses the related literature and develops empirical predictions. Section 5.3 outlines the research design. Section 5.4 presents the sample construction and the empirical findings. The final section is the conclusion.

5.2 Prior literature and empirical predictions

Concerning the prevention of selective disclosures, the MAD follows the regulatory approach of the Reg FD, the relevant US regulatory measure (e.g., Ferrarini 2004). After the introduction of the MAD, it should be more difficult for analysts with close links to firms to exploit private information and thus the regulation should induce "*a level playing field among investors*" (Mehran and Stulz 2007, p. 292) and hence reduce information asymmetries among investors (Ferrarini 2004; Avgouleas 2005). In particular, firm management could become more restrictive in providing information after the introduction of MAD, when they stop providing selective disclosures to a small privileged group of affiliated financial analysts in order to prevent public disclosures (e.g., Cornett et al. 2007; Canace et al. 2010). Thus, the effectiveness of analyst coverage could be reduced by regulatory reforms which could result in an increase in capital costs.

As outlined, the objective of the MiFID is to introduce organizational requirements ("*chinese walls*") and conduct-of-business rules for investment firms and banks in order to contain possible conflicts of interest. Also this approach should have a constraining impact on the possible "*privileged access*" (Carapeto and Gietzmann 2011, p. 757) of financial analysts to company information. Thus, both measures should effectively prevent affiliated analysts from collecting, processing and spreading this information to potential investors in the context of a seasoned equity offering.

Bowen et al. (2008) provides evidence that SEO underpricing is reduced when issuing firms are covered by analysts with “*privileged access*“ (Carapeto and Gietzmann 2011, p. 757). However, prior research on the effectiveness of Reg FD (e.g., Gintschel and Markov 2004; Mohanram and Sunder 2006; Kim and Jung 2012) suggests, that Reg FD has reduced the informativeness and accuracy of financial analysts with “*privileged access*“ (Carapeto and Gietzmann 2011, p. 757), since superior forecasting performance was based on information obtained from selective disclosures. Especially in the case of firms which are covered by affiliated analysts with “*privileged access*“ (Carapeto and Gietzmann 2011, p. 757), investors might end up with increased SEO underpricing after the introduction of MAD and MiFID, since affiliated analysts can no longer exploit private information.

Thus, I expect a reduced effectiveness of affiliated coverage before an SEO after the introduction of the MAD and the MiFID, which should result in increased SEO underpricing. (Prediction I)

Prior studies such as Hope (2003), Hail and Leuz (2006), Gupta et al. (2013) and Arand et al. (2015), which exploit “*cross-sectional variation*” (Leuz and Wysocki 2016, p. 571) in the regulatory environment across countries, provide evidence of a significant impact of stricter sanctions or investor protection laws on analyst forecasts and cost of capital.

Moreover, Dubois et al. (2014) and Christensen et al. (2016) provide evidence of the role of enforcement rigidity and sanction severity on the outcome of introduction of the MAD and find stronger impacts in countries with more severe sanctions and stricter enforcement.

Thus, I expect the effectiveness of affiliated coverage before an SEO after the introduction of the MAD to be reduced greater in countries with more severe sanctions on infringements of the MAD. ***(****Prediction II****)***

5.3 Research design and data

5.3.1 Identification strategy and econometric model

$$UP = \beta_0 + \beta_1 \, RegIndicator + \beta_2 \, AFF\_COV + \beta_3 \, RegIndicator \times AFF\_COV + \sum \beta_j \, Controls_j + \sum \beta_j \, Fixed\ Effects_j + \varepsilon \qquad (1)$$

$$UP = \beta_0 + \beta_1 \, RegIndicator + \beta_2 \, COV\_IND + \beta_3 \, AFF\_COV + \beta_4 \, RegIndicator \times AFF\_COV + \beta_5 \, RegIndicator \times COV\_UNAFF + \sum \beta_j \, Controls_j + \sum \beta_j \, Fixed\ Effects_j + \varepsilon \qquad (2)$$

$$UP = \beta_0 + \beta_1 \, MAD + \beta_2 \, RegAttribute + \beta_3 \, AFF\_COV + \beta_4 \, MAD \times RegAttribute + \beta_5 \, MAD \times AFF\_COV + \beta_6 \, RegAttribute \times AFF\_COV + \beta_7 \, MAD \times RegAttribute \times AFF\_COV + \sum \beta_j \, Controls_j + \sum \beta_j \, Fixed\ Effects_j + \varepsilon \qquad (3)$$

My identification strategy for measuring the impact of the introduction of the MAD and MiFID on the effectiveness of coverage by affiliated financial analysts in the context of SEOs applies a Difference-in-Difference (DiD) regression design and exploits, in the case of the MAD, the unique features of the European Regulatory setting.

When investigating a regulatory change, a DiD-design controls the common trends, which are time-variant and affect both the treated and untreated group but which are not caused by the regulatory reform itself (the introduction of the MAD or MiFID in my setting) (Guan et al. 2012, p. 448; Roberts and Whited 2013, pp. 520-531).

In addition to the DiD-design, the staggered implementation of the MAD as outlined, strengthens the empirical approach and should further facilitate an accurate identification of the impact of the MAD, since it diminishes the potential impact of confounding regulatory reforms and other confounding market-wide events as well as considerations respective the endogeneity of the timing of the implementation of regulatory reforms (Dubois et al. 2014, p. 502).

Moreover, I follow the view of Dubois et al (2014) and consider the country of a firm`s primary listing as the relevant jurisdiction when, in the case of cross border activities, administrative authorities from different countries are responsible. Dubois et al (2014) provide anecdotal evidence and conduct several robustness tests which support their point of view.

Following Lehmann (2016), my DiD-design includes one treatment group (SEOs with affiliated coverage) and different control groups. Thus, *AFF_COV* is defined as the treatment assignment indicator variable in my DiD-design, taking the value of one when the main underwriters(s) (“bookrunner(s)”) of a firm`s SEO also provided research coverage in the year prior to the SEO and zero otherwise.

RegIndicator is the post-treatment indicator variable, taking the value of one when an SEO takes place after the MAD or the MiFID has been implemented in a country and otherwise zero. Accordingly, the indicator variable *RegIndicator*× *AFF_COV* takes the value of one, when an SEO with affiliated coverage, takes place after the post-treatment period and otherwise zero.

SEOs with pure unaffiliated coverage within the year prior to the SEO are taken as my first control group (C1). The second control group is formed by SEOs with no analyst coverage within the year prior to the SEO (C2). A third control group is formed by combining control groups C1 and C2 (C1+C2).

In my DiD-design, I consider both groups as relevant: both SEOs with no analyst coverage and SEOs with pure unaffiliated coverage, since both groups should be unaffected by the reduced average informational precision which should occur when affiliated financial analysts lose their "*privileged access*" (Carapeto and Gietzmann 2011, p. 757) to firm information after the introduction of relevant regulatory measures.[58] However, the MAD, could cause, like the comparable Reg FD, a so-called "*chilling effect*" (e.g., Koch et al. 2013), which implies that overall supply of firm-specific information to covering financial analysts and investors could be reduced by the MAD. Such an overall effect of the MAD would affect all SEOs in the sample and is not restricted to treated SEOs or SEOs from the control groups.

In order to test my empirical *Prediction I*, the models 1 and 2 are specified. Both models include SEO underpricing (UP) as the dependent variable. Model 1 is a more conventional model including the interaction term *RegIndicator×AFF_COV* as the variable of interest. Model 2 is a "*total-effects model*" following the approach of Christensen et al. (2013b). In this specification, two distinct groups *RegIndicator×AFF_COV* and *RegIndicator× COV_UNAFF* are created separately in the post-regulation period, indicating the impact of the introduction of the *RegIndicator* (MAD or MiFID) on the underpricing of SEOs with affiliated coverage and SEOs with solely unaffiliated coverage separate.

[58] Bowen et al. (2008) exclude SEOs with no coverage by financial analysts from their sample when investigating the incremental impact of coverage by affiliated analysts. This specification is comparable to my regressions based on my control group C1. Bowen et al. (2008, p. 680) argue that the impact of coverage by analysts affiliated with the main underwriter of the SEO is not obvious, when there are SEOs with no prior analyst in the sample. However, in my DiD-Design, I consider SEOs with no prior analyst coverage as a suitable control group, since such SEOs should, as outlined, be unaffected by the regulatory reforms, except a possible overall impact of the so-called "*chilling effect*" (e.g., Koch et al. 2013).

My empirical *Prediction II* is tested with model 3, which follows the more conventional approach with the interaction term *MAD×RegAttribute×AFF_COV* as the variable of interest.[59]

The indicator variable *RegAttribute* creates two distinct groups in the post-MAD period: One group for countries with high sanction severity or supervisory powers and a second group for the remaining countries. See Table 5.1 and Table 5.2 for details concerning the regulatory attributes. Thus, the indicator variable *MAD× RegAttribute× AFF_COV* captures the impact of differences in sanction severity and supervisory power among the sample countries on the underpricing of treated SEOs in the post-treatment period.

The indicator variables of my DiD-design are added to a comprehensive set of control variables at the firm-level. My fixed effects structure includes industry-, year- and country-fixed effects and thus follows relevant prior literature (Bowen et al. 2008; Huang and Zhang 2011; Gupta et al. 2013).

5.3.2 Variable measurement

In regression models 1-3, SEO underpricing (*UP*) is calculated as: ((P-OP)/P) x100, where P is defined as the last stock price of a firm available in Datastream before an SEO and OP represents the offer price. This definition follows Bowen et al. (2008) and Huang and Zhang (2011).

The coverage intensity (*COV*) is defined as the natural logarithm of one plus the number of unique broker research units which cover a firm within the year prior to an SEO.[60] Typically,

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[59] Thus, my approach follows Christensen et al. (2013b), who apply models of this conventional type as an alternative to their "*total effects models*". See also Barth and Israeli (2013).

[60] I/B/E/S, the database used in this study, provides different identifiers for brokerage firms and investment banks, whose analysts issue stock recommendations and target prices. Separate research units (e.g., separate units for small cap and large cap research or national affiliates) of one brokerage firm/investment bank can be identified with the help of the I/B/E/S Broker Code identifier (See Appendix I for more details on this aspect).

there is one analyst per broker research unit covering a firm, thus my definition should be in line with Bowen et al. (2008), who measure coverage at the analyst-level.

Affiliated Coverage (*AFF_COV*) is an indicator variable, taking the value of one when the main underwriter(s) ("*bookrunner(s)*") of a firm`s SEO also provided research coverage within the year prior to the SEO and zero otherwise. Definition follows largely Bowen et al. (2008). Unaffiliated Coverage Only (*COV_UNAFF*) is an indicator variable, taking the value of one when at least one broker research unit covers a firm within the year prior to an SEO but no coverage by the main underwriter(s) ("*bookrunner(s)*") of a firm`s SEO is provided in this period of time and otherwise zero.

Coverage indicator (*COV_IND*) is an indicator variable, taking the value of one when at least one broker research unit covers a firm within the year prior to an SEO and otherwise zero. The variable *RegIndicator* is defined either as MAD or MiFID, which are implemented as indicator variables, taking the value of one when the relevant directive is implemented in a member country and zero otherwise.[61]

The indicator variable *RegAttribute* creates two distinct groups in the post-MAD or post-MiFID period: one group for countries with high sanction severity and supervisory powers and a second group for the remaining countries. The measures "*Sanction Severity of MAD*" (SANC_SEV) and "*Supervisory Power*" (S_POWER) were obtained from Dubois et al. (2014) and Christensen et al. (2016).

SANC_SEV is an indicator variable, taking the value of one when the rank of the sanction severity index by Dubois et al. (2014) in country c is below the sample median and otherwise zero. The sample countries "*are ranked based on their respective administrative pecuniary penalties, criminal sanctions, and fines ([MAD] articles 4, 6.3, 6.5, and 14.3). For each country, the average rank for the three sorts of sanctions is the sanction severity index*" Dubois et al. (2014, p.525). Countries are ranked from 1 (highest sanction severity) to 12 (lowest sanc-

[61] Table 5.1 shows the Entry-into-force dates of the MAD and the MiFID.

tion severity) by Dubois et al. (2014). S_POWER is an indicator variable, taking the value of one, when the count of positive answers (in a questionnaire answered by European regulators concerning their competences in case of MAD) is above the sample median and zero otherwise.

Following the relevant literature (e.g., Corwin 2003; Bowen et al. 2008; Huang and Zhang 2011), I include several control variables in the regression model: the natural log of market capitalisation (*MCAP*), Relative offer size (*REL_SIZE*), the last stock price prior to the SEO (*LN_PRICE*) and prior stock price standard deviation (*S_VOL*) over a 250 day period before the SEO. Following Huang and Zhang (2011), standard errors are clustered at the firm-level. A detailed description of the variables can be found in Table 5.2, details concerning the regulatory attributes can be found in Table 5.1

Table 5. 1: Regulatory Attributes and Entry-into-Force Dates

Country	Regulatory Attributes		Entry-into-Force Dates	
	Sanction severity	Supervisory Power	MAD	MIFID
Austria	10	70	1-Jan-2005	1-Nov-2007
Belgium	4	69	19-Sep-2005	1-Nov-2007
Denmark	12	60	1-Apr-2005	1-Nov-2007
Finland	12	63	1-Jul-2005	1-Nov-2007
France	4	75	27-Jul-2005	2-Dec-2007
Germany	9	64	30-Oct-2004	1-Nov-2007
Ireland	4	73	6-Jul-2005	21-Nov-2007
Italy	2	70	18-May-2005	28-Nov-2007
Netherlands	7	67	1-Oct-2005	1-Nov-2007
Portugal	7	73	15-Apr-2006	1-Nov-2007
Spain	2	60	24-Nov-2005	17-Feb-2008
Sweden	11	73	1-Jul-2005	1-Nov-2007
UK	1	76	1-Jul-2005	1-Nov-2007

Table 5.1 includes information on the Entry-into-Force-Dates of the MAD and MiFID and Regulatory Attributes. More details concerning the calculation and sources of the Regulatory Attributes can be obtained from Table 5.2. Entry-into-force dates of the MAD and MiFID were obtained from the European Commission website.

Table 5. 2: Definition of Variables

Variable		Definition	Data sources
Dependent variable			
SEO Underpricing (Discount)	UP	SEO underpricing (discount) is calculated as: ((P-OP)/P) x100, where P is defined as the last stock price of a firm available in Datastream before an SEO and OP represent the offer price. Definition follows Bowen et al. (2008) and Huang and Zhang (2011).	SDC; Datastream
Independent variables: Coverage related			
Coverage Intensity	COV	The natural logarithm of one plus the number of unique broker research units in I/B/E/S, which cover a firm within the year prior to an SEO. Definition follows Bowen et al. (2008). Typically, there is one analyst per broker research unit covering a firm, thus this definition should be in line with Bowen et al. (2008), who measure coverage at the analyst level.	I/B/E/S
Coverage Indicator	COV_IND	Indicator variable, taking the value of one when at least one broker research unit in I/B/E/S covers a firm within the year prior to an SEO and otherwise zero.	I/B/E/S
Affiliated Coverage	AFF_COV	Indicator variable, taking the value of one when the main underwriter(s) ("bookrunner(s)") of a firm`s SEO also provided research coverage within the year prior to the SEO and zero otherwise. Definition follows largely Bowen et al. (2008).	I/B/E/S; SDC
Unaffiliated Coverage Only	COV_UNAFF	Indicator variable, taking the value of one when at least one broker research unit in I/B/E/S covers a firm within the year prior to an SEO but no coverage by the main underwriter (s) ("bookrunner(s)") of a firm`s SEO is provided in this period of time and otherwise zero.	I/B/E/S; SDC

(Table 5.2 continued)

Independent variables: Regulation and Regulatory Attributes			
Reg_Indicator_ 1: Market Abuse Directive	MAD	Indicator variable, taking the value of one when an SEO was conducted after the Market Abuse Directive was implemented in a country and otherwise zero.	European Commission
Reg_Indicator_ 2: Markets in Financial Instruments Directive	MiFID	Indicator variable, taking the value of one when an SEO was conducted after the Markets in Financial Instruments Directive was implemented in a country and otherwise zero.	European Commission
Sanction Severity of MAD	SANC_SEV	Indicator variable, taking the value of one when the rank of the sanction severity index by Dubois et al. (2014) in country c is below the sample median and otherwise zero. The sample countries "*are ranked based on their respective administrative pecuniary penalties, criminal sanctions, and fines ([MAD] articles 4, 6.3, 6.5, and 14.3). For each country, the average rank for the three sorts of sanctions is the sanction severity index*" (Dubois et al. 2014, p.525). Countries are ranked from 1 (highest sanction severity) to 12 (lowest sanction severity).	Dubois et al. (2014)
Supervisory Power	S_POWER	Indicator variable, taking the value of one, when the count of positive answers (in a questionnaire answered by European regulators concerning their competences in case of MAD) is above the sample median and zero otherwise.	Christensen et al. (2016)

(*Table 5.2 continued*)

Independent variables: Control variables			
Market capitalisation	LN_MCAP	The natural logarithm of market capitalization (in Million Euro) of a firm on the last day before an offer. Definition is analog to Bowen et al. (2008).	Datastream
Relative offer size	REL_SIZE	The number of shares which are offered, divided by the number of shares outstanding before the SEO. Definition is analog to Bowen et al. (2008) and Huang and Zhang (2011).	Datastream; SDC
Last stock price pre issue	LN_PRICE	The natural logarithm of the last stock price on the day before an SEO. Definition is analog to Bowen et al. (2008) and Huang and Zhang (2011).	Datastream
Prior stock price standard deviation	S_VOL	Standard deviation of daily stock returns of a firm over a 250 day period before the offer date. Approach is analog to Bowen et al. (2008).	Datastream
Industry indicator	IBSCT	Industry indicators are based on the I/B/E/S industry sector classification (IBSCT).	I/B/E/S
Fixed effects structure: industry-, (issue)year- and country-fixed effects; standard errors clustered at the firm-level.			I/B/E/S; Datastream; Worldscope

5.4 Results

5.4.1 Sample construction and descriptive statistics

I examine SEOs issued within the years 1999-2011 by firms listed in the EU-15 countries. In order to align my sample with the study of Dubois et al. (2014), Greece and Luxembourg were excluded. Information on SEOs is obtained from SDC Platinum. Analyst stock recommendation data was taken from the I/B/E/S detail, stock prices and further data was obtained from Datastream and Worldscope. Information concerning sanction severity was obtained from Dubois et al. (2014) and Christensen et al. (2016). I follow Huang and Zhang (2011) and take I/B/E/S detail stock recommendations as the measure in order to determine coverage by analysts. More information concerning the matching of SDC and I/B/E/S data in order to determine affiliated coverage can be found in Appendix I.

My initial sample, containing information in all relevant data fields in SDC, includes 7926 SEOs issued within the years 1999-2011 by firms listed in 13 countries within the European Union. The sample was further reduced due to missing data in Datastream and Worldscope for firms contained in the initial SEO sample from SDC. Moreover, following Dubois et al. (2014), I exclude SEOs of firms which are not incorporated and primarily listed in the same country in order to assure the determination of relevant jurisdiction in case of cross border activities.

My further sample selection process follows Bowen et al. (2008) and Huang and Zhang (2011): In particular, SEOs have to include at least a small proportion of primary offerings. Moreover, I exclude American Depositary Receipts (ADRs), American depositary share (ADS), units, loan stocks and related types of financial instruments. SEOs with extreme underpricing (where absolute value of UP is more than 50%) are excluded, too. My final sample includes 3937 SEOs.[62]

Furthermore, like Bowen et al. (2008), Huang and Zhang (2011) and other relevant prior studies such as Corwin (2003) and Altınkılıç and Hansen (2003), I apply their offer day correction procedure (due to incorrect offer dates in SDC Platinum): I "*designate the day after the SDC offer date as the offer date if the trading volume on the day after the SDC offer date is more than twice the trading volume on the SDC offer date and is more than twice the average daily volume over the previous 250 days"* (Huang and Zhang 2011, p.150).

Tables 5.3 and 5.4 provide further details concerning descriptive statistics, correlation coefficients and sample composition. As can be seen in Table 5.3, 31,1% of the SEOs in the

[62] When calculating the analyst coverage prior to SEOs, I exclude, following the approach of Dubois et al. (2014), stock recommendations issued probably due to stock recommendation rating system changes, since they cannot be considered as real coverage. See chapter 3.5.1 for more details. In addition to my selection criteria, Huang and Zhang (2011) exclude preferred shares. Moreover, Bowen et al. (2008) and Huang and Zhang (2011) exclude small (stock price below 3$) and illiquid (stock price above 400$) stocks.

sample have affiliated coverage (*AFF_COV*), 36% have pure unaffiliated coverage (*COV_UNAFF* - forming control group 2 in the DiD-design), while 32,9% of the SEOs in the sample have no analyst coverage at all (forming control group 1 in the DiD-design).

Table 5.4 provides an overview of my SEO sample. Two aspects are of importance. While both Table 5.4 Panel A and B show that my sample is dominated by SEOs issued by firms with their primary listing in the UK, a comparison of both panels shows that multiple SEOs by one single firm within one year are contained in my sample.

Table 5. 3: Descriptive Statistics

Table 5.3, Panel A: Descriptive statistics

	mean	min	p25	p50	p75	max
UP	10.757	-50.000	2.124	7.143	17.808	50.000
MAD	0.519	0.000	0.000	1.000	1.000	1.000
MIFID	0.387	0.000	0.000	0.000	1.000	1.000
AFF_COV	0.311	0.000	0.000	0.000	1.000	1.000
COV_IND	0.671	0.000	0.000	1.000	1.000	1.000
COV_UNAFF	0.360	0.000	0.000	0.000	1.000	1.000
COV	1.137	0.000	0.000	1.099	1.946	3.689
LN_MCAP	5.023	-1.833	3.264	4.932	6.675	11.771
S_VOL	0.037	0.000	0.020	0.031	0.046	1.026
REL_SIZE	0.244	0.000	0.045	0.100	0.261	29.322
LN_PRICE	3.456	-3.219	2.169	3.519	4.848	10.431

(continued)

(Table 5.3 continued)

Table 5.3, Panel B: Pearson's correlation coefficients												
		1	2	3	4	5	6	7	8	9	10	11
UP	1	1.00										
MAD	2	0.08***	1.00									
MIFID	3	0.08***	0.77***	1.00								
AFF_COV	4	0.03*	0.15***	0.15***	1.00							
Cov_ind	5	-0.04**	0.09***	0.07***	0.47***	1.00						
Cov_unaff	6	-0.07***	-0.06***	-0.08***	-0.50***	0.52***	1.00					
COV	7	-0.00	0.07***	0.07***	0.49***	0.76***	0.27***	1.00				
LN_MCAP	8	-0.07***	-0.02	-0.07***	0.33***	0.54***	0.21***	0.79***	1.00			
S_VOL	9	0.15***	0.02	0.13***	-0.04**	-0.13***	-0.09***	-0.13***	-0.24***	1.00		
REL_SIZE	10	0.13***	0.05**	0.00	-0.04*	-0.09***	-0.05***	-0.11***	-0.21***	0.08***	1.00	
LN_PRICE	11	-0.20***	-0.20***	-0.24***	0.07***	0.22***	0.15***	0.21***	0.43***	-0.28***	-0.11***	1.00

Table 5.3 Panel A shows the descriptive statistics for continuous and indicator variables in the baseline (Tables 5.5 and 5.6) regressions. Variables are defined in Table 5.2. Table 5.3, Panel B shows the Pearson's correlation coefficients for variables included in the baseline (Tables 5.5 and 5.6) regressions. The reported values are the coefficients (and t-values in brackets). ***, ** and * indicate significance (two-tailed) at the 1%, 5% and 10% level.

Table 5. 4: Sample Composition

Table 5.4, Panel A: Number of SEOs by Year of Issue and Country

	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	Total
Austria	5	2	4	8	2	5	5	8	14	2	5	8	6	74
Belgium	5	11	3	0	4	1	0	4	8	3	12	15	6	72
Denmark	0	0	5	5	0	6	2	8	7	7	14	12	7	73
Finland	0	4	5	4	0	7	7	3	10	3	12	7	7	69
France	5	33	28	9	11	3	16	18	37	20	43	25	21	269
Germany	34	25	15	5	19	13	15	13	23	16	31	78	44	331
Ireland	0	1	6	6	7	3	1	1	2	1	2	4	4	38
Italy	2	3	3	13	8	8	2	6	10	12	7	17	17	108
Netherlands	10	21	14	10	1	12	8	3	14	1	21	8	3	126
Portugal	3	4	2	4	2	4	0	1	1	3	2	1	3	30
Spain	8	9	4	5	0	9	2	1	1	2	11	3	3	58
Sweden	0	21	7	8	8	3	9	5	10	12	11	24	9	127
United Kingdom	59	209	285	209	264	272	106	102	195	267	354	140	100	2562
Total	131	343	381	286	326	346	173	173	332	349	525	342	230	3937

Table 5.4 Panel A shows the number of SEOs contained in the sample, sorted by year of issue and country.

(continued)

(Table 5.4 continued)

Table 5.4, Panel B: Number of Firms (Issuer) by Year of Issue and Country

	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011
Austria	2	1	1	3	2	4	4	6	8	1	4	3	3
Belgium	2	5	2	0	2	1	0	4	6	2	9	8	4
Denmark	0	0	5	2	0	4	2	7	6	5	11	8	4
Finland	0	2	2	3	0	4	6	2	5	2	10	7	5
France	3	20	14	8	7	2	15	17	26	13	31	22	16
Germany	13	15	8	3	12	10	13	13	19	12	23	54	34
Ireland	0	1	5	3	5	2	1	1	2	1	1	1	1
Italy	1	1	3	9	6	5	2	6	7	6	3	8	8
Netherlands	6	10	5	5	1	9	7	3	10	1	15	7	3
Portugal	1	3	2	4	2	4	0	1	1	2	1	1	2
Spain	5	5	2	3	0	4	2	1	1	2	8	2	2
Sweden	0	9	4	6	6	3	8	5	7	6	7	20	6
United Kingdom	38	136	154	116	175	189	86	85	172	176	222	100	83
Total	71	208	207	165	218	241	146	151	270	229	345	241	171

Table 5.4 Panel B shows the number of firms (issuer) contained in the sample, sorted by year of issue and country.

5.4.2 Empirical findings

Table 5.5 reports the results of the regression investigating the impact of the MAD on the effectiveness of affiliated analyst coverage (Baseline MAD – Regressions) with different regression specifications (models 1-4) over the full sample period 1999-2011. The MAD indicator by itself has a significant positive and thus increasing impact on SEO underpricing in model 2 (at the 5%-level) and model 3 (at the 10%-level), while the MiFID indicator, which is included as a control variable in all four regression models, has a significant negative (at the 5%-level) and thus reducing impact on SEO underpricing in model 2. The indicator for affiliated coverage (*AFF_COV*) has significant negative and thus reducing impact in model 1 (at the 1%-level) and in model 3 (at the 10%-level). The coverage indicator (*COV_IND*) in model 4 has a significant negative impact (at 5%-level) and thus reducing impact on SEO underpricing, while coverage intensity (COV) does not have a significant impact in model 1-4.

The control variables (*S_VOL*, *REL_SIZE*, *LN_PRICE*) are highly significant in most specifications, have their predicted signs and are thus in line with relevant prior research (e.g., Bowen et al. 2008). However, *LN_MCAP* is significant with a positive sign in model 2 (at 1%-level) and model 3 (at 5%-level), which is not in line with Bowen et al. (2008) but in line with Huang and Zhang (2011). The variable of interest in models 1-4, *MAD×AFF_COV* is significant in all four specifications (at 1%-level in models 1, 3, 4 and at 5%-level in model 2) with a positive sign and thus has an increasing impact on SEO underpricing. The *MAD × COV_UNAFF* indicator in model 4 remains insignificant.

Table 5.6 reports the results of the regression investigating the impact of the MiFID on the effectiveness of affiliated analyst coverage (baseline MiFID-regressions) with different regression specifications (models 1-4) over the full sample period 1999-2011.

Table 5. 5: Baseline MAD – Regressions

	(1)	(2)	(3)	(4)
Sample Period	1999-2011	1999-2011	1999-2011	1999-2011
MAD	-1.703	3.846**	2.885*	2.421
	(-0.80)	(2.16)	(1.71)	(1.29)
MIFID	2.008	-4.975**	-1.990	-1.867
	(0.92)	(-2.41)	(-1.16)	(-1.10)
AFF_COV	-4.160***	-0.580	-1.335*	-0.901
	(-3.07)	(-0.83)	(-1.93)	(-1.24)
COV_IND				-2.552**
				(-2.46)
COV	0.773	-0.524	-0.278	0.577
	(0.97)	(-0.76)	(-0.58)	(0.98)
MADxAFF_COV	4.341***	2.399**	3.341***	3.821***
	(3.36)	(2.32)	(3.34)	(3.00)
MADxCOV_UNAFF				0.937
				(0.77)
LN_MCAP	0.491	0.910***	0.528**	0.398
	(1.50)	(2.92)	(2.12)	(1.55)
S_VOL	28.262**	13.619	31.561***	30.551***
	(2.42)	(0.77)	(2.68)	(2.59)
REL_SIZE	1.478***	10.393***	2.087***	2.053***
	(2.70)	(5.87)	(2.73)	(2.67)
LN_PRICE	-1.531***	-0.566**	-1.407***	-1.314***
	(-5.07)	(-1.97)	(-5.75)	(-5.32)
Fixed-Effects	yes	yes	yes	yes
Control Group	C2	C1	C1+C2	C1+C2
Observations	2520	2643	3937	3937
R^2	0.134	0.202	0.131	0.133
Adjusted R^2	0.119	0.189	0.122	0.123

Notes: The relevant regression in models (1)-(3) is:

$$UP = \beta_0 + \beta_1\, RegIndicator + \beta_2\, AFF\_COV + \beta_3\, RegIndicator \times AFF\_COV + \sum \beta_j\, Controls_j + \sum \beta_j\, Fixed\ Effects_j + \varepsilon$$

The relevant regression in model (4) is:

$$UP = \beta_0 + \beta_1\, RegIndicator + \beta_2\, COV\_IND + \beta_3\, AFF\_COV + \beta_4\, RegIndicator \times AFF\_COV + \beta_5\, RegIndicator \times COV\_UNAFF + \sum \beta_j\, Controls_j + \sum \beta_j\, Fixed\ Effects_j + \varepsilon$$

The indicator variable *RegIndicator× AFF_COV* measures the DiD-effect, the impact of the introduction of the MAD or MiFID (*RegIndicator*) on underpricing of SEOs with affiliated coverage. In model 4 two distinct groups *RegIndicator × AFF_COV* and *RegIndicator × COV_UNAFF* are created in the post-regulation period, indicating separately the impact of the introduction of the *RegIndicator* (MAD or MiFID) on underpricing of SEOs with affiliated coverage and SEOs with sole unaffiliated coverage. For the definition of the variables, see Table 5.2. The DiD-designs of the regression models contain different control groups, as indicated. The regression models include country-, industry- and year-fixed effects, if indicated. Standard errors are clustered at the firm-level. The reported values are the coefficients (and t-values in brackets). ***, ** and * indicate significance (two-tailed) at the 1%, 5% and 10% level.

Table 5. 6: Baseline MiFID – Regressions

	(1)	(2)	(3)	(4)
Sample Period	1999-2011	1999-2011	1999-2011	1999-2011
MAD	1.220	5.059***	4.248***	4.317***
	(0.63)	(3.03)	(2.67)	(2.70)
MIFID	0.160	-6.605***	-3.152*	-2.696
	(0.07)	(-3.09)	(-1.79)	(-1.41)
AFF_COV	-3.261***	-0.706	-1.073*	-0.927
	(-2.60)	(-1.15)	(-1.77)	(-1.47)
COV_IND				-1.769*
				(-1.86)
COV	0.688	-0.563	-0.300	0.498
	(0.85)	(-0.82)	(-0.63)	(0.85)
MIFIDxAFF_COV	3.968***	3.548***	3.879***	3.425**
	(2.84)	(3.12)	(3.57)	(2.47)
MIFIDxCOV_UNAFF				-0.672
				(-0.51)
LN_MCAP	0.488	0.909***	0.520**	0.399
	(1.49)	(2.92)	(2.09)	(1.55)
S_VOL	28.465**	13.340	31.402***	30.815***
	(2.46)	(0.76)	(2.68)	(2.63)
REL_SIZE	1.415***	10.356***	2.048***	2.015***
	(2.59)	(5.88)	(2.69)	(2.62)
LN_PRICE	-1.534***	-0.588**	-1.414***	-1.322***
	(-5.05)	(-2.04)	(-5.77)	(-5.33)
Fixed-Effects	yes	yes	yes	yes
Control Group	C2	C1	C1+C2	C1+C2
Observations	2520	2643	3937	3937
R^2	0.133	0.204	0.132	0.134
Adjusted R^2	0.118	0.191	0.123	0.124

Notes: The relevant regression in models (1)-(3) is:

$$UP = \beta_0 + \beta_1\, RegIndicator + \beta_2\, AFF\_COV + \beta_3\, RegIndicator \times AFF\_COV + \sum \beta_j\, Controls_j + \sum \beta_j\, Fixed\ Effects_j + \varepsilon$$

The relevant regression in model (4) is:

$$UP = \beta_0 + \beta_1\, RegIndicator + \beta_2\, COV\_IND + \beta_3\, AFF\_COV + \beta_4\, RegIndicator \times AFF\_COV + \beta_5\, RegIndicator \times COV\_UNAFF + \sum \beta_j\, Controls_j + \sum \beta_j\, Fixed\ Effects_j + \varepsilon$$

The indicator variable *RegIndicator× AFF_COV* measures the DiD-effect, the impact of the introduction of the MAD or MiFID (*RegIndicator*) on underpricing of SEOs with affiliated coverage. In model 4 two distinct groups *RegIndicator × AFF_COV* and *RegIndicator × COV_UNAFF* are created in the post-regulation period, indicating separately the impact of the introduction of the *RegIndicator* (MAD or MiFID) on underpricing of SEOs with affiliated coverage and SEOs with sole unaffiliated coverage . For the definition of the variables, see Table 5.2. The DiD-designs of the regression models contain different control groups, as indicated. The regression models include country-, industry- and year-fixed effects, if indicated. Standard errors are clustered at the firm-level. The reported values are the coefficients (and t-values in brackets). ***, ** and * indicate significance (two-tailed) at the 1%, 5% and 10% level.

Table 5. 7: MAD-Implementation – Regressions

	(1)	(2)	(3)	(4)	(5)	(6)
Sample Period	1999-2011	1999-2011	1999-2011	1999-2011	1999-2011	1999-2011
RegAttribute	SANC_SEV	SANC_SEV	SANC_SEV	S_POWER	S_POWER	S_POWER
MAD	-0.838	6.003***	4.628**	-2.890	5.023**	3.867*
	(-0.21)	(2.80)	(2.24)	(-0.75)	(2.30)	(1.86)
MIFID	1.981	-4.868**	-1.961	2.005	-4.799**	-1.937
	(0.91)	(-2.36)	(-1.14)	(0.92)	(-2.32)	(-1.13)
AFF_COV	-2.889	0.084	-0.335	-5.279	-0.818	-0.983
	(-0.85)	(0.06)	(-0.25)	(-1.60)	(-0.64)	(-0.75)
MADxAFF_COV	4.119	1.244	2.279	5.716	2.066	2.702
	(1.05)	(0.62)	(1.09)	(1.57)	(1.12)	(1.45)
MADxRegAttribute	-0.935	-2.728*	-2.100	1.284	-1.537	-1.176
	(-0.25)	(-1.66)	(-1.32)	(0.36)	(-0.94)	(-0.77)
MADxRegAttribute xAFF_COV	-0.099	1.282	1.046	-1.563	0.350	0.684
	(-0.02)	(0.55)	(0.44)	(-0.40)	(0.16)	(0.31)
RegAttribute xAFF_COV	-1.145	-0.667	-1.091	1.217	0.454	-0.354
	(-0.35)	(-0.44)	(-0.70)	(0.39)	(0.30)	(-0.23)
Fixed-Effects	yes	yes	yes	yes	yes	yes
Controls	yes	yes	yes	yes	yes	yes
Control Group	C2	C1	C1+C2	C2	C1	C1+C2
Observations	2520	2643	3937	2520	2643	3937
R^2	0.135	0.203	0.132	0.134	0.203	0.132
Adjusted R^2	0.119	0.189	0.122	0.118	0.189	0.121

(Continued)

(Table 5.7 continued)

Notes: The relevant regression model is:

$$UP = \beta_0 + \beta_1 \, MAD + \beta_2 \, RegAttribute + \beta_3 \, AFF\_COV + \beta_4 \, MAD \times RegAttribute + \beta_5 \, MAD \times AFF\_COV + \beta_6 \, RegAttribute \times AFF\_COV + \beta_7 \, MAD \times RegAttribute \times AFF\_COV + \sum \beta j \, Controls_j + \sum \beta j \, Fixed\ Effects_j + \varepsilon$$

The indicator variable *RegAttribute* creates two distinct groups in the post-MAD period: One group for countries with high sanction severity or supervisory powers and a second group for the remaining countries. See Table 5.1 and Table 5.2 for details concerning the regulatory attributes. Thus, the indicator variable *MAD* × *RegAttribute* × *AFF_COV* captures the impact of differences in sanction severity and supervisory powers between the sample countries on underpricing of treated SEOs in the post-treatment period. The DiD-designs of the regression models contain different control groups, as indicated. The regression models include relevant controls (LN_MCAP, S_VOL, REL_SIZE, LN_PRICE), country-, industry- and year-fixed effects, if indicated.Standard errors are clustered at the firm-level. The reported values are the coefficients (and t-values in brackets). ***, ** and * indicate significance (two-tailed) at the 1%, 5% and 10% level.

The results in Table 5.6 show comparable outcomes to the MAD-regressions in Table 5.5. The MAD-indicator by itself has a significant positive impact in models 2, 3 and 4 (at the 1%-level in each case). The MiFID-indicator has a significant negative impact in model 2 (at the 1%-level) and model 3 (at the 5%-level). *AFF_COV* is significant with negative sign (at the 1%-level) in model 1 and in model 3 (at the 10%-level). The coverage indicator (*COV_IND*) is weakly significant with a negative sign in model 4. Again, coverage intensity (*COV*) does not have a significant impact. Moreover, also in the case of the baseline MiFID-regressions, the control variables (*S_VOL*, *REL_SIZE*, *LN_PRICE*) are highly significant in most specifications, have their predicted signs and are thus in line with relevant prior research (e.g., Bowen et al. 2008).

Furthermore, *LN_MCAP* is again significant with a positive sign in model 2 (at 1%-level) and model 3 (at 5%-level). The variable of interest in models 1-4, *MIFID×AFF_COV*, is significant in all four specifications (at 1%-level in models 1-3 and at 5%-level in model 4) with a positive sign and thus has an increasing impact on SEO underpricing. The *MIFID×COV_UNAFF* indicator in model 4 remains insignificant.

Table 5.7 reports the results of the regression investigating the influence of regulatory attributes on the impact of MAD on the effectiveness of affiliated analyst coverage (MAD-implementation-regressions) with different regression specifications (models 1-6) over the full sample period 1999-2011. The main effect (indicator *RegAttribute*) was dropped in the regressions, since it was absorbed by country-fixed effects in models 1-6. In all six regression specifications, the indicator variable *MAD×RegAttribute×AFF_COV* remains insignificant.

5.4.3 Discussion of findings

The results in Table 5.5 and 5.6 provide evidence for a reduced effectiveness of affiliated coverage before an SEO after the introduction of the MAD and the MiFID, which results in increased SEO underpricing in affected SEOs. Moreover, the findings of my DiD-design are consistent for three different control groups. Therefore, my results are in line with *prediction I*. After the introduction of the regulatory measures, the competitive advantage of affiliated analysts vanished. Thus, this would imply that in the case of firms which are covered by affiliated analysts with "*privileged access*" (Carapeto and Gietzmann 2011, p. 757), investors might end up with increased SEO underpricing after the introduction of MAD and MiFID, since affiliated analysts can no longer provide their superior reports. Moreover my results are in line with prior research on Reg FD, which provided evidence that the informativeness and accuracy of financial analysts with *"privileged access*" (Carapeto and Gietzmann 2011, p. 757) was reduced after the selective disclosures were banned by Reg FD (e.g., Gintschel and Markov 2004; Mohanram and Sunder 2006; Kim and Jung 2012).

The significant positive impact of the MAD indicator by itself has to be interpreted with some caution but can be seen as evidence for the existence of the so-called "*chilling effect*" in relevant literature (e.g., Koch et al. 2013), which implies that the overall supply of firm-specific information to covering financial analysts and investors could have been reduced by the MAD. The significant negative impact of the MiFID indicator in some regression specifications has to be interpreted with even more caution since the MiFID was not introduced in a staggered way like the MAD but in one very narrow window, November/December 2007, (with the exemption of Spain) thus weakening the identifiability of a causal effect brought about by MiFID (Christensen et al. 2016).

The insignificant results in Table 5.7 indicate that differences in sanction severity and supervisory powers between the sample countries do not have an impact on underpricing of treated SEOs in the post-treatment period. Thus, my results are not in line with *prediction II*.

5.4.4 Robustness tests

Three different tests are applied in order to evaluate the robustness of my regression results. First of all, SEOs issued by firms with primary listing in the UK are excluded from the sample, sample since firms from this country dominate the baseline sample. The regression results are reported in Tables 5.8 and 5.9. The results remain qualitatively the same as in the full sample. The indicators *MAD×AFF_COV* and *MIFID×AFF_COV* are significant and have their predicted positive sign. Secondly, I reduce the sample period to the pre-MiFID years 1999-2007 in order to investigate the impact of the MAD in a shorter window. The results are reported in Table 5.10. The indicator of interest *MAD×AFF_COV* remains significant in model 1 (at the 5%-level) and in model 4 (at the 10%-level). Thus the results in the shorter pre-MiFID sample period are weaker than in the full sample. Thirdly, a balanced sample is constructed, which includes only firms, which already had an SEO before the year 2008, in order to rule out the impact of new issuers, who joined the sample after the year 2007. The results are reported in Table 5.11 and Table 5.12. The indicators *MAD×AFF_COV* and *MIFID×AFF_COV* have their predicted positive sign and are significant in most regression specifications, but at a reduced significance level. Thus, the results are partly driven by the new firm, which did not issue equity capital before the year 2008.

Table 5. 8: Robustness – MAD excl. UK

	(1)	(2)	(3)	(4)
Sample Period	1999-2011	1999-2011	1999-2011	1999-2011
MAD	-9.571**	1.008	-0.919	-4.405
	(-2.20)	(0.35)	(-0.29)	(-1.12)
MIFID	-0.926	-3.867	-3.487	-3.254
	(-0.24)	(-1.23)	(-1.19)	(-1.12)
AFF_COV	-7.684**	-1.620	-2.923**	-2.298*
	(-2.35)	(-1.35)	(-2.33)	(-1.82)
COV_IND				-4.451
				(-1.58)
COV	-1.116	-0.406	-1.185	-0.618
	(-0.89)	(-0.38)	(-1.52)	(-0.63)
MADxAFF_COV	8.918***	3.390**	5.105***	8.625***
	(3.08)	(2.13)	(3.15)	(2.96)
MADxCOV_UNAFF				4.620
				(1.57)
LN_MCAP	1.605***	1.372***	1.358***	1.242***
	(2.95)	(2.95)	(3.31)	(2.83)
S_VOL	-0.164	6.550	6.609	2.456
	(-0.02)	(0.21)	(1.05)	(0.37)
REL_SIZE	2.110	21.633***	3.644	3.622
	(0.99)	(10.30)	(1.10)	(1.11)
LN_PRICE	-0.204	0.351	-0.387	-0.362
	(-0.35)	(0.76)	(-0.92)	(-0.86)
Fixed-Effects	yes	yes	yes	yes
Control Group	C2	C1	C1+C2	C1+C2
Observations	825	1185	1375	1375
R^2	0.245	0.334	0.208	0.211
Adjusted R^2	0.205	0.310	0.183	0.185

Notes: The relevant regression in models (1)-(3) is:

$$UP = \beta_0 + \beta_1\, RegIndicator + \beta_2\, AFF\_COV + \beta_3\, RegIndicator \times AFF\_COV + \sum \beta_j\, Controls_j + \sum \beta_j\, Fixed\ Effects_j + \varepsilon$$

The relevant regression in model (4) is:

$$UP = \beta_0 + \beta_1\, RegIndicator + \beta_2\, COV\_IND + \beta_3\, AFF\_COV + \beta_4\, RegIndicator \times AFF\_COV + \beta_5\, RegIndicator \times COV\_UNAFF + \sum \beta_j\, Controls_j + \sum \beta_j\, Fixed\ Effects_j + \varepsilon$$

The indicator variable *RegIndicator× AFF_COV* measures the DiD-effect, the impact of the introduction of the MAD or MiFID (*RegIndicator*) on underpricing of SEOs with affiliated coverage. In model 4 two distinct groups *RegIndicator × AFF_COV* and *RegIndicator × COV_UNAFF* are created in the post-regulation period, indicating separately the impact of the introduction of the *RegIndicator* (MAD or MiFID) on underpricing of SEOs with affiliated coverage and SEOs with sole unaffiliated coverage. For the definition of the variables, see Table 5.2. The DiD-designs of the regression models contain different control groups, as indicated. The regression models include country-, industry- and year-fixed effects, if indicated. Standard errors are clustered at the firm-level. The reported values are the coefficients (and t-values in brackets). ***, ** and * indicate significance (two-tailed) at the 1%, 5% and 10% level.

Table 5. 9: Robustness – MiFID excl. UK

	(1)	(2)	(3)	(4)
Sample Period	1999-2011	1999-2011	1999-2011	1999-2011
MAD	-2.199	2.782	1.508	1.679
	(-0.59)	(1.02)	(0.51)	(0.57)
MIFID	-7.705*	-5.557*	-5.754*	-9.520**
	(-1.70)	(-1.71)	(-1.91)	(-2.55)
AFF_COV	-6.186**	-1.022	-2.123**	-1.590
	(-2.14)	(-1.02)	(-2.01)	(-1.50)
COV_IND				-4.063*
				(-1.72)
COV	-1.200	-0.451	-1.242	-0.664
	(-0.96)	(-0.42)	(-1.60)	(-0.68)
MIFIDxAFF_COV	9.153***	3.468**	5.420***	9.435***
	(3.19)	(2.11)	(3.25)	(3.29)
MIFIDxCOV_UNAFF				5.450*
				(1.89)
LN_MCAP	1.589***	1.373***	1.350***	1.230***
	(2.96)	(2.95)	(3.30)	(2.83)
S_VOL	1.566	3.586	6.552	3.195
	(0.19)	(0.12)	(1.04)	(0.50)
REL_SIZE	2.177	21.633***	3.655	3.688
	(1.01)	(10.26)	(1.11)	(1.13)
LN_PRICE	-0.153	0.304	-0.411	-0.345
	(-0.26)	(0.65)	(-0.98)	(-0.81)
Fixed-Effects	yes	yes	yes	yes
Control Group	C2	C1	C1+C2	C1+C2
Observations	825	1185	1375	1375
R^2	0.248	0.334	0.209	0.214
Adjusted R^2	0.207	0.310	0.185	0.188

Notes: The relevant regression in models (1)-(3) is:

$UP = \beta_0 + \beta_1\, RegIndicator + \beta_2\, AFF\_COV + \beta_3\, RegIndicator \times AFF\_COV + \sum \beta_j\, Controls_j + \sum \beta_j\, Fixed\ Effects_j + \varepsilon$

The relevant regression in model (4) is:

$UP = \beta_0 + \beta_1\, RegIndicator + \beta_2\, COV\_IND + \beta_3\, AFF\_COV + \beta_4\, RegIndicator \times AFF\_COV + \beta_5\, RegIndicator \times COV\_UNAFF + \sum \beta_j\, Controls_j + \sum \beta_j\, Fixed\ Effects_j + \varepsilon$

The indicator variable *RegIndicator× AFF_COV* measures the DiD-effect, the impact of the introduction of the MAD or MiFID (*RegIndicator*) on underpricing of SEOs with affiliated coverage. In model 4 two distinct groups *RegIndicator × AFF_COV* and *RegIndicator × COV_UNAFF* are created in the post-regulation period, indicating separately the impact of the introduction of the *RegIndicator* (MAD or MiFID) on underpricing of SEOs with affiliated coverage and SEOs with sole unaffiliated coverage. For the definition of the variables, see Table 5.2. The DiD-designs of the regression models contain different control groups, as indicated. The regression models include country-, industry- and year-fixed effects, if indicated. Standard errors are clustered at the firm-level. The reported values are the coefficients (and t-values in brackets). ***, ** and * indicate significance (two-tailed) at the 1%, 5% and 10% level.

Table 5. 10: Robustness – MAD Sample Period 1999-2007

	(1)	(2)	(3)	(4)
Sample Period	1999-2007	1999-2007	1999-2007	1999-2007
MAD	-1.414	4.842***	3.390**	2.257
	(-0.63)	(2.65)	(1.98)	(1.16)
MIFID	1.546	-5.435**	-2.327	-2.206
	(0.70)	(-2.58)	(-1.31)	(-1.25)
AFF_COV	-3.163**	-0.239	-0.799	-0.513
	(-2.00)	(-0.35)	(-1.18)	(-0.73)
COV_IND				-1.565
				(-1.36)
COV	0.541	-0.952	-0.426	0.109
	(0.52)	(-1.11)	(-0.71)	(0.15)
MADxAFF_COV	3.192**	0.530	1.486	2.575*
	(1.99)	(0.41)	(1.20)	(1.66)
MADxCOV_UNAFF				1.848
				(1.22)
LN_MCAP	0.327	0.986***	0.419	0.342
	(0.81)	(2.59)	(1.35)	(1.08)
S_VOL	33.917*	43.047	39.148**	38.488**
	(1.87)	(1.53)	(2.16)	(2.12)
REL_SIZE	1.362***	9.274***	1.857**	1.860**
	(2.62)	(4.19)	(2.50)	(2.49)
LN_PRICE	-1.515***	-0.623*	-1.441***	-1.389***
	(-4.09)	(-1.92)	(-4.91)	(-4.66)
Fixed-Effects	yes	yes	yes	yes
Control Group	C2	C1	C1+C2	C1+C2
Observations	1526	1603	2491	2491
R^2	0.142	0.188	0.131	0.132
Adjusted R^2	0.119	0.167	0.117	0.118

Notes: The relevant regression in models (1)-(3) is:

$UP = \beta_0 + \beta_1\ RegIndicator + \beta_2\ AFF\_COV + \beta_3\ RegIndicator \times AFF\_COV + \sum \beta_j\ Controls_j + \sum \beta_j\ Fixed\ Effects_j + \varepsilon$

The relevant regression in model (4) is:

$UP = = \beta_0 + \beta_1\ RegIndicator + \beta_2\ COV\_IND + \beta_3\ AFF\_COV + \beta_4\ RegIndicator \times AFF\_COV + \beta_5\ RegIndicator \times COV\_UNAFF + \sum \beta_j\ Controls_j + \sum \beta_j\ Fixed\ Effects_j + \varepsilon$

The indicator variable *RegIndicator× AFF_COV* measures the DiD-effect, the impact of the introduction of the MAD or MiFID (*RegIndicator*) on underpricing of SEOs with affiliated coverage. In model 4 two distinct groups *RegIndicator × AFF_COV* and *RegIndicator × COV_UNAFF* are created in the post-regulation period, indicating separately the impact of the introduction of the *RegIndicator* (MAD or MiFID) on underpricing of SEOs with affiliated coverage and SEOs with sole unaffiliated coverage. For the definition of the variables, see Table 5.2. The DiD-designs of the regression models contain different control groups, as indicated. The regression models include country-, industry- and year-fixed effects, if indicated. The sample period includes the years 1999-2007. Standard errors are clustered at the firm-level. The reported values are the coefficients (and t-values in brackets). ***, ** and * indicate significance (two-tailed) at the 1%, 5% and 10% level.

Table 5. 11: Robustness – MAD Balanced Sample

	(1)	(2)	(3)	(4)
Sample Period	1999-2011	1999-2011	1999-2011	1999-2011
MAD	-1.867	4.022**	2.891*	2.165
	(-0.86)	(2.25)	(1.71)	(1.12)
MIFID	1.688	-5.419***	-2.206	-2.115
	(0.77)	(-2.64)	(-1.27)	(-1.22)
AFF_COV	-2.588*	-0.336	-0.891	-0.582
	(-1.72)	(-0.49)	(-1.29)	(-0.81)
COV_IND				-1.610
				(-1.47)
COV	-0.147	-1.012	-0.669	-0.144
	(-0.15)	(-1.26)	(-1.19)	(-0.21)
MADxAFF_COV	3.742**	1.631	2.512**	3.231**
	(2.45)	(1.38)	(2.16)	(2.15)
MADxCOV_UNAFF				1.259
				(0.90)
LN_MCAP	0.438	0.978***	0.523*	0.444
	(1.12)	(2.72)	(1.79)	(1.48)
S_VOL	30.763*	19.453	33.975**	33.323**
	(1.86)	(0.95)	(2.26)	(2.21)
REL_SIZE	1.530**	9.599***	2.097**	2.085**
	(2.58)	(5.02)	(2.51)	(2.49)
LN_PRICE	-1.604***	-0.827***	-1.502***	-1.450***
	(-4.57)	(-2.62)	(-5.44)	(-5.19)
Fixed-Effects	yes	yes	yes	yes
Control Group	C2	C1	C1+C2	C1+C2
Observations	1893	1996	3019	3019
R^2	0.141	0.184	0.131	0.132
Adjusted R^2	0.121	0.166	0.118	0.119

Notes: The relevant regression in models (1)-(3) is:

$$UP \;=\; \beta_0 + \beta_1\, RegIndicator + \;\beta_2\, AFF\_COV + \beta_3\, RegIndicator \times AFF\_COV \;+ \sum \beta_j\, Controls_j \;+ \sum \beta_j\, Fixed\ Effects_j \;+ \varepsilon$$

The relevant regression in model (4) is:

$$UP = = \beta_0 + \beta_1\, RegIndicator + \;\beta_2\, COV\_IND \;+ \beta_3\, AFF\_COV + \beta_4\, RegIndicator \times AFF\_COV + \beta_5\, RegIndicator \times COV\_UNAFF \;+ \sum \beta_j\, Controls_j \;+ \sum \beta_j\, Fixed\ Effects_j \;+ \varepsilon$$

The indicator variable *RegIndicator× AFF_COV* measures the DiD-effect, the impact of the introduction of the MAD or MiFID (*RegIndicator*) on underpricing of SEOs with affiliated coverage. In model 4 two distinct groups *RegIndicator × AFF_COV* and *RegIndicator × COV_UNAFF* are created in the post-regulation period, indicating separatel the impact of the introduction of the *RegIndicator* (MAD or MiFID) on underpricing of SEOs with affiliated coverage and SEOs with sole unaffiliated coverage. For the definition of the variables, see Table 5.2. The DiD-designs of the regression models contain different control groups, as indicated. The regression models include country-, industry- and year-fixed effects, if indicated. The sample includes only firms, which already had an SEO before the year 2008 (balanced sample). Standard errors are clustered at the firm-level. The reported values are the coefficients (and t-values in brackets). ***, ** and * indicate significance (two-tailed) at the 1%, 5% and 10% level.

Table 5. 12: Robustness – MiFID Balanced Sample

	(1)	(2)	(3)	(4)
Sample Period	1999-2011	1999-2011	1999-2011	1999-2011
MAD	0.636	4.867***	3.928**	3.954**
	(0.33)	(2.89)	(2.46)	(2.47)
MIFID	0.048	-7.093***	-3.258*	-2.432
	(0.02)	(-3.24)	(-1.79)	(-1.13)
AFF_COV	-1.681	-0.496	-0.660	-0.650
	(-1.21)	(-0.81)	(-1.09)	(-1.04)
COV_IND				-0.828
				(-0.82)
COV	-0.254	-1.047	-0.677	-0.237
	(-0.26)	(-1.31)	(-1.21)	(-0.34)
MIFIDxAFF_COV	3.574*	3.758**	3.639**	2.763
	(1.74)	(2.33)	(2.32)	(1.35)
MIFIDxCOV_UNAFF				-1.546
				(-0.81)
LN_MCAP	0.439	0.990***	0.521*	0.461
	(1.12)	(2.77)	(1.78)	(1.54)
S_VOL	31.025*	19.679	33.862**	33.745**
	(1.90)	(0.98)	(2.27)	(2.25)
REL_SIZE	1.465**	9.545***	2.057**	2.050**
	(2.48)	(5.04)	(2.47)	(2.44)
LN_PRICE	-1.611***	-0.851***	-1.514***	-1.455***
	(-4.56)	(-2.69)	(-5.47)	(-5.20)
Fixed-Effects	yes	yes	yes	yes
Control Group	C2	C1	C1+C2	C1+C2
Observations	1893	1996	3019	3019
R^2	0.140	0.187	0.132	0.133
Adjusted R^2	0.120	0.169	0.119	0.119

Notes: The relevant regression in models (1)-(3) is:

$$UP = \beta_0 + \beta_1 \, RegIndicator + \beta_2 \, AFF\_COV + \beta_3 \, RegIndicator \times AFF\_COV + \sum \beta_j \, Controls_j + \sum \beta_j \, Fixed \ Effects_j + \varepsilon$$

The relevant regression in model (4) is:

$$UP = = \beta_0 + \beta_1 \, RegIndicator + \beta_2 \, COV\_IND + \beta_3 \, AFF\_COV + \beta_4 \, RegIndicator \times AFF\_COV + \beta_5 \, RegIndicator \times COV\_UNAFF + \sum \beta_j \, Controls_j + \sum \beta_j \, Fixed \ Effects_j + \varepsilon$$

The indicator variable *RegIndicator× AFF_COV* measures the DiD-effect, the impact of the introduction of the MAD or MiFID (*RegIndicator*) on underpricing of SEOs with affiliated coverage. In model 4 two distinct groups *RegIndicator × AFF_COV* and *RegIndicator × COV_UNAFF* are created in the post-regulation period, indicating separately the impact of the introduction of the *RegIndicator* (MAD or MiFID) on underpricing of SEOs with affiliated coverage and SEOs with sole unaffiliated coverage. For the definition of the variables, see Table 5.2. The DiD-designs of the regression models contain different control groups, as indicated. The regression models include country-, industry- and year-fixed effects, if indicated. The sample includes only firms, which already had an SEO before the year 2008 (balanced sample). Standard errors are clustered at the firm-level. The reported values are the coefficients (and t-values in brackets). ***, ** and * indicate significance (two-tailed) at the 1%, 5% and 10% level.

5.5 Conclusion

This study investigates the question whether European regulatory measures, the Market Abuse Directive (MAD), which bans selective disclosures (e.g., Ferrarini 2004) as well as the Markets in Financial Instruments Directive (MiFID), which includes organizational requirements ("*chinese walls*") and conduct-of-business rules for investment banks (e.g., Enriques 2006), reduce the effectiveness of coverage by analysts with close links to firms ("*affiliated analysts*") in reducing the discounting of seasoned equity offerings (SEOs), which is known as "*SEO Underpricing*" in the literature (e.g., Altınkılıç and Hansen 2003; Corwin 2003; Mola and Loughran 2004; Huang and Zhang 2011; Gupta et al. 2013). My findings provide evidence for a reduced effectiveness of affiliated coverage after the introduction of the MAD and the MiFID, which results in increased SEO underpricing in affected SEOs. Thus, after the introduction of the regulatory measures, the competitive advantage of affiliated analysts vanishes. Thus, the SEO setting is a very specific setting in which the provision of selective disclosures to affiliated financial analysts could be of advantage for firms raising new equity capital, since affiliated analyst coverage can help to reduce SEO underpricing. This study provides evidence that the regulatory measures which are geared up to prevent the transfer of private information from firms to affiliated financial analysts, reduced the effect of affiliated analyst coverage in the context of SEOs. This result can be interpreted as an "*unintended consequence*" (Brüggemann et al. 2012; Leuz and Wysocki 2016, p. 531) of the introduction of MAD and MiFID, since the reduced effectiveness of affiliated coverage in mitigating SEO underpricing results in an increased discount and thus higher capital costs for firms when raising new equity capital. However, as can be seen in one of the robustness tests, the results of DiD regressions are partly driven by new firms, which did not issue equity capital before the year 2008. Moreover, the results of my regressions provide evidence that differences between the sample countries in sanction severity and supervisory powers concerning the MAD do not have an impact on the underpricing of treated SEOs in the post-treatment period.

6. Conclusion

6.1 Summary of main results

By utilizing the advantages of the European regulatory setting, this dissertation investigates the impact of the outlined European regulatory measures MAD and MiFID on sell-side financial analysts‘ behaviour and on the information environment.

In respect of the regulation of conflicts of interest of sell-side financial analysts, this dissertation investigates the impacts of Article 6(5) of the MAD, Article 13 of the MiFID and relevant articles in the implementing directives which refer to these articles. Study 1 investigates whether optimism and informativeness of affiliated analysts’ target prices are influenced by regulatory measures which are geared up to mitigate conflicts of interest of sell-side analysts. As Dubois et al. (2014), I can show that the MAD had a mitigating impact on over-optimism in affiliated analysts’ stock recommendations. However, concerning optimism in target prices, I find a highly significant positive impact of the regulatory measures MAD and MiFID on the target price optimism of affiliated analysts. Thus, the results imply that the regulatory measures introduced have provoked a trade-off between the quantitative analyst metrics stock recommendations and target prices. In the post-regulation period, financial analysts concentrate on biasing target prices, which are a less visible measure for sending an overly optimistic opinion, since the disclosure requirements of the MAD are geared more explicitly towards stock recommendations. Moreover, I cannot find a reduced informativeness of affiliated target price revisions in the post-regulation period, which implies that market participants cannot see through the incentives of affiliated analysts properly since they do not discount target price revisions thoroughly.

In respect of the prohibition of selective disclosures, the impact of Article 6(3) of the MAD is investigated. Concerning the impact of the prevention of selective disclosures on expectations management, the results of Study 2 show that the MAD did not have a significant constraining impact on the amount or incidence of expectations management. Thus, my results differ from the findings of Das et al. (2011), who find a significant reducing impact of the Reg FD on expectations management. The findings of Study 3 indicate that the prohibition of selective disclosures by the MAD results in a reduced effectiveness of affiliated coverage in the context of SEOs. Thus, the results of Study 3 augment the prior findings of Bowen et al. (2008), who find a reducing impact of affiliated analyst coverage on SEO underpricing, but do not investigate the impact of the Reg FD on affiliated analyst coverage in their sample of US firms. Moreover, the results of Study 3 provide evidence that the organisational requirements ("*chinese walls*") and conduct-of-business rules for investment banks of the MiFID, which are geared up to mitigate conflicts of interest (e.g., Enriques 2006), also reduce the effectiveness of coverage by affiliated analysts in the context of seasoned equity offerings (SEOs).

Thus, in conclusion, the results of my three empirical studies provide mixed evidence concerning the question whether the regulatory objectives of the MAD and MIFID were achieved. While prior research in the European regulatory setting (Dubois et al. 2014) as well as comparable studies in the US (Kadan et al. 2009) can provide evidence that the over-optimism in affiliated analysts' stock recommendations is successfully reduced by regulatory measures, the results of Study 1 show that this is not achieved in the case of affiliated analysts' target prices. I interpret my results as an indication of an "*avoidance strategy*" (Leuz and Wysocki 2016, p. 536) applied by financial analysts, who have an economic incentive to bias their research outputs even in the post-regulation period. After the introduction of the MAD, it is less risky for analysts to bias their target prices, since the disclosure requirements of the MAD are geared more explicitly towards stock recommendations. The prevention of selective disclosures by the MAD did not have an overall impact on expectations management, as the results of Study 2 show. However, the results of Study 2 do not necessarily imply that the MAD did not successfully mitigate the prevalence of selective disclosures. Study 3 provides evidence that the regulatory measures which are geared up to prevent the transfer of private information from firms to affiliated financial analysts, reduced the effect of affiliated analyst coverage in the context of SEOs. This result can be interpreted as an "*unintended consequence*" (Brüggemann et al. 2012; Leuz and Wysocki 2016, p. 531) of the introduction of MAD and MiFID, since the reduced effectiveness of affiliated coverage in mitigating SEO underpricing results in an increased discount and thus higher capital costs for firms when raising new equity capital.

The coherent research question, whether differences in sanction severity influence the outcome of regulatory reforms, is addressed by all three studies. Again, results are mixed. Study 1 does not find any significant impact of differences in the regulatory quality or sanction severity across the sample countries on target price optimism. Thus, the "*avoidance strategy*" (Leuz and Wysocki 2016, p. 536) applied by financial analysts does not seem to be amplified by more severe sanctions. Study 2 finds some evidence that countries, which introduced severe sanctions for infringements of the MAD and extensive competences for regulatory authorities, experienced a stronger mitigating impact of the MAD. Thus, this weak evidence is in line with related prior research such as Dubois et al. (2014) and Christensen et al. (2016). In Study 3, differences in sanction severity and supervisory powers between the sample countries do not have an impact on the effectiveness of affiliated coverage after the introduction of the MAD.

6.2 Main limitations of the empirical studies

The results of the empirical studies in this dissertation are subject to several limitations. Firstly, the matching of I/B/E/S and SDC data, which is the basis for identifying the affiliation relationships between the sell-side financial analysts and covered firms in Study 1 and Study 3, follows the well established approach of recent papers like Kolasinski and Kothari (2008), Dubois et al. (2014) and Malmendier and Shanthikumar (2014). Moreover I follow the approach of Loh (2009, p. 12) and adjust the matching of I/B/E/S and SDC data on a yearly basis, which refines the precision of my matching approach. However, this does not result in a perfect identification of affiliation relationships, which would require an adjustment on a daily basis. Another limitation of my matching approach, which uses the backfilled SDC "Parent Company" data fields in order to identify M&As among broker firms, is that only those parent-subsidiary relationships can be identified systematically which continue to exist up to the present.

Secondly, in Study 1 and Study 3 I cannot filter out brokerage firms contained in I/B/E/S which do not have a subsidiary or their main office in the European Union within the sample period. A brokerage firm without a subsidiary or their main office within the European Union would not be affected by the European regulatory measures (Dubois and Dumontier 2008, p. 12). However, it seems implausible that such firms should have a large proportion of the sample, since large investment banks are typically represented with an office in several EU member countries. Smaller brokerage firms contained in my sample of I/B/E/S data are typically local brokerage firms which originate from one of the sample countries.

Thirdly, it is possible that capital market participants in Europe were informed about conflicts of interest by existing national disclosure rules and by the US regulatory measures, which were introduced several years before the MAD made the disclosure of conflicts of interest compulsory for financial institutions active in EU member countries. Hovakimian and Saenyasiri (2014) point out that several of the relevant US regulatory measures also have to be applied by Non-US brokerage firms and banks. Moreover, Hovakimian and Saenyasiri (2014) provide evidence that US-based brokerage firms and banks may also apply with the relevant US regulation abroad. There is evidence that analyst reports about firms listed in European countries included a disclosure section about existing conflicts of interest of the issuing brokerage firm also in the pre-MAD period. These disclosure sections were, for example, based on existing national disclosure rules or on US regulatory meausures.[63] However, Dubois et al. (2014) cannot find any significant impact of the US regulatory measures on sell-side financial analysts' behaviour in their European sample.

Fourthly, since I cannot identify different types of investors, the research design in Study 1 cannot answer the question, whether the "*avoidance strategy*" (Leuz and Wysocki 2016, p. 536) is targeted at a certain type of shareholder, such as retail investors, or at a certain type of institutional investor as in the study by Bilinski et al. (2015).

6.3 Avenues for further research

The empirical studies in this dissertation open up several avenues for further research, which can be categorized into three different scopes.

First, since prior research provided evidence that biased analyst research outputs have the capability to mislead in particular small investors (e.g., Malmendier and Shanthikumar 2007; Mikhail et al. 2007), it would be of interest to see how different types of investors react to stock recommendations and target prices in the post-regulation period. Moreover, as pointed out in the previous section, the "*avoidance strategy*" (Leuz and Wysocki 2016, p. 536), which was detected in Study 1, could be targeted at a certain type of shareholder.

Second, the studies in this dissertation concentrate on the common quantitative outputs of sell-side financial analysts. Prior research (e.g., Twedt and Rees 2012) also investigated the textual components of analyst reports. Thus, it would be of interest to see whether analysts also react to the regulatory measures in the textual analysis of their written research reports, since over-optimism could be relocated and thus be reflected in the tone of the textual components of the reports after the introduction of the MAD and MiFID.

[63] See Appendix II for more details.

Third, in 2017 and 2018 the MiFID II becomes active and should therefore open up new avenues for research.[64] The MiFID II could have a drastic impact on the sell-side research analysts, since it challenges the business model of sell-side research business (Mellow 2016). Brokerage firms and investment banks employing sell-side analysts could be forced to unbundle sell-side research costs from trade commission after the introduction of the MiFID II, which could result in a reduced demand for sell-side research reports (Mellow 2016; Meager 2017).

[64] Detailed information concerning implementation dates of all components of the MiFID II is available on the website of the European Commission.

7. Appendix I

Matching Data from I/B/E/S and SDC Platinum

Affiliation identification strategy - An Outline

An empirical investigation of equity analysts' conflicts of interests and the links between broker firms and covered firms requires an appropriate identification strategy. A well-established stream of literature uses data from SDC Platinum, which includes information about IPOs, SEOs and M&A transactions. Moreover, the SDC database includes the names of investment banks and financial advisory firms, which acted as underwriters (managers of equity and debt issuances) or M&A advisors in these transactions. These data items can be matched to earnings forecasts, target prices or stock recommendations from I/B/E/S or First Call, in order to identify which forecasts and recommendations were issued by analysts working for these underwriters or financial advisory firms.[65]

Typically, these studies consider analysts and their employing broker firms to be affiliated, when these broker firms were involved as underwriters or advisors in an IPO, SEO or M&A transaction of the covered firm within a certain period of time before or after a stock recommendation, a target price or a forecast was issued (e.g., Kolasinski and Kothari 2008; Kadan et al. 2009; Dubois et al. 2014).[66]

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[65] This stream of literature includes recent papers like Haushalter and Lowry (2011), Dubois et al. (2014) and Malmendier and Shanthikumar (2014). Other relevant papers which match I/B/E/S and SDC data are for instance Lin and McNichols (1998), Hong and Kubik (2003), Cowen et al. (2006), Ljungqvist et al. (2007), Malmendier and Shanthikumar (2007), Cornett et al. (2007), Kolasinski and Kothari (2008), Kadan et al. (2009), Loh (2009), McKnight et al. (2010), Bradley et al. (2012), Guan et al. (2012) and Kim and Jung (2012). Furthermore, James and Karceski (2006) and O'Brien et al. (2005), who both use analyst data from First Call, apply an equivalent matching approach.

[66] In IBES, all firms that contribute stock recommendations, target prices and other forecasts are referred to as brokers/estimators (Thomson Reuters 2010). Relevant studies using I/B/E/S data usually use the term broker (e.g., Kadan et al. 2009; Dubois et al. 2014), too. However, as shown by Cowen et al. (2006) and Barber et al. (2007), broker firms included in I/B/E/S can be categorized into investment banks, brokerage firms and research firms. Cowen et al. (2006) and Barber et al. (2007) use the data items from SDC described above to categorize broker firms to which extent these firms acted as securities underwriters. I follow the relevant literature and use the term broker, when referring to firms that provide stock recommendations, target prices and forecasts to I/B/E/S and when referring to firms which are included as providers of securities underwriting or M&A advisory services in SDC Platinum.

Usually, names of broker firms from I/B/E/S and SDC for the same institution are not written identically. However, in most cases they are written in a very similar way and thus could be assigned unambiguously.[67] Nevertheless, M&A transactions between broker firms, parent-subsidiary relationships and name changes of broker firms during the sample period complicate the matching procedure.

In I/B/E/S, broker firms are included with their most recent name (Cowen et al. 2006, p. 127; Wu and Zang 2009, p. 67). Historical broker firms (indicated as "historical" in many cases), which were the target of an M&A transaction, renamed or closed down, are also included in I/B/E/S. SDC includes the names of broker firms (providers of securities underwriting or M&A advisory services) which were applicable at the respective time of an equity/debt issuance or M&A transaction (SDC data fields "Managers" in case of equity/debt issuances and "Acquiror Advisors"/"Target Advisors" in case of M&A transactions) and relevant updated parent company names of the broker firms (SDC data fields "Manager's Parent" and "Parent of Acquiror Advisor"/"Parent of Target Advisor"). The SDC "Parent Company" data fields are backfilled after name changes and M&A transactions between broker firms and therefore provide information about "*the current subsidiary or merger relationships of the bank*" (Loh 2009, p. 12). Thus, the current parent company of a broker firm is also included in the SDC "Parent Company" data fields in the years before the respective M&A transaction between a broker firm and its new owner took place (Loh 2009, p. 12).[68]

I follow the approach of recent papers like Kolasinski and Kothari (2008), Loh (2009), Haushalter and Lowry (2011), Dubois et al. (2014) and Malmendier and Shanthikumar (2014), who manually match I/B/E/S data and SDC data on the basis of I/B/E/S broker names and the names of securities' underwriters or M&A advisors from SDC in order to identify

[67] A typical example is "COMMERZBANK CORPORATES & MKTS" (I/B/E/S name) and "Commerzbank Capital Markets" (SDC name).
[68] This handling of data items in the SDC database was approved by Thomson Reuters in 2014.

stock recommendations, earnings forecasts or target prices issued by analysts from affiliated broker firms.

Kolasinski and Kothari (2008) match I/B/E/S brokers with the names of M&A advisors from SDC. They improve their matching by consulting sources like Lexis-Nexis and corporate web sites in order to identify parent-subsidiary relationships (Kolasinski and Kothari 2008, p. 827). Malmendier and Shanthikumar (2014) and Malmendier and Shanthikumar (2007) include the Kolasinski and Kothari (2008) mapping in their matching procedures. As has been outlined above, M&A transactions between broker firms complicate the matching procedure. This is due to the affiliations of broker firms which were the target of an M&A transaction. Such affiliations can be caused by securities underwriting or M&A advisory services provided by broker firms. These affiliations are inherited by the surviving/successor broker firm (James and Karceski 2006, p. 6; Loh 2009, p. 12).

For instance, when French Bank BNP took control of Paribas and formed BNP Paribas SA in 2000, the affiliations of Paribas were inherited by the successor firm BNP Paribas SA. When matching IBES and SDC data, existing affiliations of the acquiring company BNP have to be accounted for. Moreover, the affiliations of the acquired Bank Paribas have to be assigned to BNP Paribas as of the merger. In order to account for mergers systematically during the sample period, I follow the approach of Loh (2009, p. 12) and use the backfilled SDC “Parent Company” data fields in order to identify M&As among broker firms and to adjust my matching of I/B/E/S and SDC data on a yearly basis. Affiliations are inherited by the surviving/successor broker firm as of the merger year.

Table A1: Matching procedure of I/B/E/S and SDC data

Panel A: Illustration of the matching procedure of I/B/E/S Names and SDC Names

Case	I/B/E/S Full Names	SDC Parent Company	SDC Manager/M&A Advisor	Year of M&A between Broker firms
(1)	Broker A	Broker A	Broker A	n.a.
(2)	Broker B (Historical)	Broker A	Broker B	(2002)
(3)	Broker A	Broker A	Broker B	2002

Panel B: Example for relations between Broker Full Names and Broker Codes in I/B/E/S

	I/B/E/S Full Names	I/B/E/S Broker Code
(a)	BNP PARIBAS	BNPFH
(b)	BNP PARIBAS	PARIBEU
(c)	BNP PARIBAS	BNPED
(d)	BNP PARIBAS SECURITIES SINGAPORE PTE LTD	BNPFS

Panel C: Example for relations between SDC Parent Company Names and SDC Manager/ M&A Advisor Names

	SDC Parent Company	SDC Manager/M&A Advisor	Year of M&A between Broker firms
(a)	BNP Paribas SA	BNP Paribas Securities Corp	n.a.
(b)	BNP Paribas SA	BNP Capital Markets	n.a.
(c)	BNP Paribas SA	Paribas Capital Markets	2000
(d)	BNP Paribas SA	Banque Generale du Luxembourg	2009

Table A1, Panel A, outlines the three possible matches of I/B/E/S and SDC data, which are identified in the matching procedure. Column "I/B/E/S" contains the names of the brokers in I/B/E/S, columns "SDC Parent Company" and "SDC Manager/M&A Advisor" contain corresponding names from SDC. Column "Year of M&A" contains the year in which Broker B was aquired by Broker A.
Table A1, Panel B, provides an example for the relations between Broker full names and broker masked codes in I/B/E/S on the basis of BNP Paribas. In rows (a) to (c) different I/B/E/S Broker Codes, representing different research units within BNP Paribas, are linked to the same Broker Full Name. Typically, as illustrated in row (d), an I/B/E/S Broker Code is linked to one I/B/E/S Full Name. All rows (a) to (d) have to be considered as part of BNP Paribas Group, when linking I/B/E/S Full Names and SDC Names, as illustrated in Panel A.
Table A1, Panel C, provides an example for the relations between SDC "Parent Company" Names and SDC "Manager/M&A Advisor" Names. BNP Paribas was formed after the acquisition of Paribas by BNP. Thus, no merger years have to be determined in row (a) and row (b), since the unit "BNP Paribas Securities Corp" did not exist before the merger and "BNP Capital Markets" was already part of acquirer BNP before the acquisition of Paribas. In row (c) and row (d), the units "Paribas Capital Markets" and "Banque Generale du Luxembourg" become part of BNP Paribas SA as of the years of acquisition of those units by BNP and BNP Paribas SA respectively.

Description of matching procedure

Table A1, Panel A, outlines three possible matches of I/B/E/S and SDC data, which can be identified in my matching procedure. In the simplest scenario (*case 1*), a broker (Broker A) continues to exist during the whole sample period and was not the target of an M&A transaction. *Case 1* broker firms can be matched by assigning I/B/E/S broker names to applicable SDC "Parent Company" names. In *case 2*, a historical broker firm (Broker B) was, in this example, the target of an M&A transaction and was acquired by Broker A in the year 2002. In this case, the relevant backfilled SDC "Parent Company" data field would show "Broker A". However, in *case 2* broker names can be matched by linking the historical I/B/E/S broker name of Broker B with the applicable name of Broker B in the SDC "Manager/M&A Advisor" field, since in this case both data items include the historical firm name.

Additionally, solely name changes of broker firms can be identified when searching for *case 2* matches. For instance, WestLB was renamed Portigon AG in 2012. Accordingly, the broker name "WESTLB RESEARCH (HISTORICAL)" in I/B/E/S can be matched to the applicable historical names in the SDC "Manager/M&A Advisor" fields. However, solely name changes which were not caused by M&As have to be treated as *case 1*. Thus, I/B/E/S broker name "WESTLB RESEARCH (HISTORICAL)" is linked to the SDC "Parent Company" name "Portigon AG".

A manual match is possible in *case 1* and *case 2*, since broker names from I/B/E/S and the relevant SDC data fields for an identical institution are written in a very similar way and thus can be assigned unambiguously in most cases. In some cases, several SDC "Parent Company" or SDC "Manager/M&A Advisor" names have to be assigned respectively to one I/B/E/S broker name. This is due to parent-subsidiary relationships and name changes. Furthermore, in some cases, a broker house is included in I/B/E/S with several entries (e.g., with several subsidiaries in different countries). In these cases, relevant SDC "Parent Company" or SDC

“Manager/M&A Advisor” names are assigned to each relevant I/B/E/S entry respectively, since affiliations may not be restricted to one subsidiary of a broker firm.[69]

Events like *case 3* in Table A1, Panel A further increase complexity in the matching procedure of relevant I/B/E/S and SDC names and require a refinement of *case 1* matches. In *case 3*, an existing affiliation of Broker B has to be taken into account, since this relationship is inherited by the acquiring Broker A as of the year of the M&A transaction (year 2002 in this example). In order to account for inherited affiliations, the backfilled SDC “Parent Company” data is used to identify M&As among broker firms systematically. This identification process is done in several steps and by using different sources of information on M&A transactions between broker firms:

First, the SDC “Parent Company” names for all matches of category *case 1* and corresponding names in the SDC data field “Manager/M&A Advisor” are collected for the relevant sample period 1996-2011. Typically, there are several observations with different names in the SDC data field “Manager/M&A Advisor” corresponding to an identical SDC “Parent Company” name. All observations can be dropped, in which the company names in the SDC “Parent Company” and SDC “Manager/M&A Advisor” field are identical to each other, since this indicates that no merger has taken place.

Second, a manual comparison of the remaining observations in the two data fields has to be conducted, since the SDC “Manager/M&A Advisor” field can contain subsidiary companies of the relevant parent company. Thus, the names in the SDC “Manager/M&A Advisor” field have to be categorized into simple name variations (e.g., a national affiliate), name changes or subsidiaries which were the result of M&As. Pure name variations can be dropped, while the latter two categories have to be checked manually. I follow Cueni and Fiechter (2013) and

[69] Unsurprisingly, most items in the SDC “Manager/M&A Advisor” field are linked to one SDC Parent respectively. However, in some cases SDC contains several items for an identical broker firm group also in the SDC “Parent Company” data field. E.g., SEB is included in data field SDC Parent name with "SEB Group” and “SEB Enskilda”.

Loh (2009) and use information about M&As between broker firms from tables, figures and appendixes in Bao and Edmans (2011), Hong and Kacperczyk (2010), Ljungqvist et al. (2006) and Corwin and Schultz (2005). A reasonable number of M&As among broker firms can be identified with the help of these studies. In order to identify further M&As, information was obtained from various reliable internet sources such as corporate websites and financial press sites. Moreover, additional information on relevant broker mergers and M&A dates is obtained from the SDC database by following the sample selection approaches of Hong and Kacperczyk (2010) and Wu and Zang (2009) and thus generating a list of M&As in the relevant sample period, industries and countries. This list was used to identify further M&As.

Third, cases can be dropped, which could be verified as pure name changes. For identified broker mergers, the exact years of the M&A transactions are collected from the above sources. Thus, for matches of category *case 3* this refined matching procedure allows for the mapping of inherited affiliations as of the year of the M&A transaction.

Additionally, I verify and refine my matching by following Wu and Zang (2009, pp. 67-68, p. 84), who use the I/B/E/S Broker Code data field "BAID", which contains abbreviated short names for broker firms. The "BAID" data field is included in I/B/E/S as a broker identifier, in addition to number codes (BACODE) and the full names of broker firms.[70] Wu and Zang (2009) detect some cases in their manually matched sample of broker firm mergers, in which recommendations or forecasts are issued under the number codes (BACODE) and Broker Code (BAID) of historical I/B/E/S brokers after these were acquired by another broker. The authors assume that analyst research departments of these historical brokers remain as separate units within the acquiring broker houses. Thus, the Broker Code (BAID) data items

[70] The I/B/E/S items BAID and BACODE (notation of Wu and Zang (2009)) are referred to as Estimator ID (BAID) and Estimator Mask Code (BACODE) in I/B/E/S (Thomson Reuters 2010). Moreover, they are referred to as Broker Code (BAID) and Broker Mask Code (BACODE) when accessing I/B/E/S data via Thomson Reuters Advanced Analytics. I use the term Broker Code for the I/B/E/S data item BAID.

can be passed over to the new entity after M&A transactions and thus can provide further insights into which historic brokers' research units are continued by acquiring firms.[71]

Table A1, Panel B, provides an example for the relations between I/B/E/S Broker Full Names and I/B/E/S Broker Codes on the basis of BNP Paribas SA. In rows (a) to (c) of Panel B, different I/B/E/S Broker Codes, representing different research units within BNP Paribas SA, are linked to the same I/B/E/S Broker Full Name. Typically, as illustrated in row (d), an I/B/E/S Broker Code is linked to one I/B/E/S Full Name. All rows (a) to (d) have to be considered as part of BNP Paribas SA, when linking I/B/E/S Full Names and SDC Names, as illustrated in Panel A. Row (c) represents a case in which research unit "PARIBEU" of historical broker firm Paribas continues to exist after Paribas was acquired by BNP. Such cases further complicate the matching of I/B/E/S and SDC data in two different but interconnected ways.

First, I/B/E/S recommendations and target prices issued under one I/B/E/S Broker Code can be linked to different broker firms at different points in time. However, this is difficult to detect, since broker firms are typically included with their most recent I/B/E/S Broker Full Name. For instance, I/B/E/S includes individual stock recommendations issued under broker code "PARIBEU" until year 2004. As of year 2000 (the year in which BNP Paribas SA was formed), "PARIBEU" is part of BNP Paribas SA. However, in the years before the year 2000 stock recommendations issued under broker code "PARIBEU" are associated with historical broker firm Paribas. Like the matching approach of Kolasinski and Kothari (2008), my matching approach of I/B/E/S and SDC data only identifies parent-subsidiary relationships which continue to exist up to the present in *case 1* and *case 3*. Thus, I/B/E/S Broker Codes of historic broker firms have to be linked to SDC data via *case 2*. In the case of "PARIBEU", stock recommendations and target prices issued under this I/B/E/S Broker Code before the year

[71] Identification of Broker Codes (BAID) items in I/B/E/S is straightforward in many cases, as illustrated in Table A1, Panel B. However, in some cases, it is not possible to identify a broker firm based on the I/B/E/S Broker Code data field.

2000 can be renamed to I/B/E/S Broker Code "PARIBED". "PARIBED" is linked to I/B/E/S Full Name "PARIBAS (GERMANY) CAPITAL MARKETS", a research unit of Paribas which was not continued by BNP Paribas and thus can be linked to relevant SDC names via *case 2*.

Second, M&A transactions between broker firms which are captured via *case 3* require the determination of a "Merger Perspective" in I/B/E/S. This is straightforward in simple cases. For example, when an M&A advisory company without an equity research unit is acquired by a full-service investment bank, which had already run a research unit before the M&A transaction and continues to do so afterwards. In this simple case, the M&A is accounted for with the acquiring investment bank as the starting point. Inherited affiliations in SDC of the acquired firm are accounted for as of the merger year and are linked to the stock recommendations and target prices issued by analysts of the aquiror's equity research unit.

A more complex case is outlined in Table A1, Panel C. As has been pointed out above, BNP Paribas SA was formed after the acquisition of Paribas by BNP. Thus, M&As are accounted for with BNP as the starting point in this example. No merger years have to be determined in row (a) and row (b) of Table A1, Panel C, since the unit "BNP Paribas Securities Corp" did not exist before the merger and "BNP Capital Markets" was already part of acquirer BNP before the acquisition of Paribas. In row (c) and row (d) of Table A1, Panel C, the units "Paribas Capital Markets" and "Banque Generale du Luxembourg" become part of BNP Paribas SA as of the years of acquisition of those units by BNP and BNP Paribas SA respectively. Additionally, as already shown in Panel B of Table A1, I/B/E/S Broker Codes representing separate research units are linked to BNP Paribas SA. If these research units do not originate from BNP, they have to be renamed in the years before the merger, as described in the case of "PARIBED".

Thus, in the case of more complex M&A transactions, in which research units of both merged entities continue to function after the transaction, a "Merger Perspective" has to be determined in I/B/E/S. Thus, I compare all I/B/E/S Full Names and corresponding I/B/E/S Broker Codes and identify cases in which research units of acquired companies continue to exist under the acquirer. As outlined in the case of “PARIBEU” in Panel C of Table A1, I/B/E/S Broker Codes of such research units which have been carried over, have to be changed to another broker code of the same historic broker firm for the years before the relevant M&A year. If this is not possible, they are changed to the Pseudo-Broker Code “NEUTRAL”.

Discussion of the matching procedure

By following the approach of recent papers like Kolasinski and Kothari (2008), Loh (2009), Haushalter and Lowry (2011), Dubois et al. (2014) and Malmendier and Shanthikumar (2014), my manual matching approach is in line with the relevant literature. Furthermore, following the approach of Loh (2009, p. 12) and adjusting my matching of I/B/E/S and SDC data on a yearly basis, I can further refine the precision of my matching approach. However, this does not result in a perfect identification of affiliations, which would require an adjustment on a daily basis.

Another limitation of my matching approach, which uses the backfilled SDC “Parent Company” data fields in order to identify M&As among broker firms, is that only those parent-subsidiary relationships can be identified systematically which continue to exist up to the present. For instance, “Wasserstein Perella Group Inc” was bought by Dresdner Bank AG in 2001. In 2009, Dresdner Bank AG was acquired by Commerzbank AG. Thus, the SDC “Manager/M&A Advisor” field shows “Wasserstein Perella Group Inc” and the corresponding SDC “Parent Company” field shows “Commerzbank AG”. If relevant historic I/B/E/S broker firms can be identified, such cases are accounted for in relevant *case 2* matches.

Moreover, my approach is comparable to the procedure applied by Dubois et al. (2014), who use monthly snaphots of I/B/E/S data and match this I/B/E/S data to SDC manager/advisor names of equity/debt issuances and M&A transactions. Since broker firms are included in I/B/E/S with their most recent names in each monthly I/B/E/S snapshot, M&A transactions between broker houses and name changes can be identified by comparing the monthly I/B/E/S snapshots.[72]

[72] Details concerning their matching approach were provided by the authors upon request.

8. Appendix II

Disclosure of Conflicts of Interests in the pre-MAD period

To the best of my knowledge, it is an open question, as to what extent capital market participants in Europe were informed about sell-side analysts' conflicts of interest by the disclosure rules introduced by different jurisdictions within the European Union and by the newly introduced US regulations, before the MAD made the disclosure of conflicts of interest compulsory for financial institutions active in EU member countries. For instance, Hovakimian and Saenyasiri (2014) provide evidence that brokerage firms and banks governed by US regulations, also apply the relevant rules (Global Settlement and NASD Rule 2711) in sell-side research reports about firms listed in other countries. Table A2 provides evidence of an investigation into sell-side analyst research reports obtained from the Investext database about the two largest German listed firms and the largest Swedish listed firm, according to their market capitalization (in Datastream) at the end of 2003.[73] Germany and Sweden were taken, because German law already included a conflict of interest disclosure rule for financial analysts before the introduction of the MAD, while there was no such regulation in Sweden in the pre-MAD period (Forum Group 2003).

Four sample selection criteria were applied. Firstly, the analyst research reports have to be issued within the time frame of after the introduction of the last of the relevant US regulatory measures and before the introduction of the MAD in the respective country.[74] Secondly, the research reports have to be issued by brokerage firms or investment banks.[75] Thirdly, the research reports have to be written in English. Fourthly, I have followed Demirakos et al. (2004) and Demirakos et al. (2010) who exclude short reports of under a minimum number of

[73] Investext also includes conference call transcripts and industry reports. Such reports are excluded from the investigation. Moreover, analyst research reports without a textual component are also excluded.
[74] 29.04.2003, the entry-into-force date of the global settlement is considered as the beginning of the sample period (see Hovakimian and Saenyasiri 2014, for details concerning the entry-into-force dates of relevant US regulatory measures). The sample period ends on 30.09.2004 (for the German firms) and on 30.06.2005 (for the Swedish firm).
[75] Thomson Reuters provides a list of Non-Brokerage Firms. Research reports issued by analysts employed by one of these firms are excluded from the sample.

pages from their sample. I require reports to have more than 14 pages and thus exclude rather short reports[76], which often do not include a full conflicts of interest disclosure section. After applying these selection criteria, the final sample includes 194 sell-side analyst research reports.

Table A2 shows, whether sell-side analyst research reports in the sample include a conflicts of interest disclosure section. Moreover, it determines under which legal basis conflicts of interest are disclosed. The indicators *Disc_German*, *Disc_USA*, *Disc_UK* take the value of one, when a disclosure section included in an analyst research report is based on German-, US- or British law and otherwise zero, respectively. The indicator *Disc_Global* takes the value of one when a general combined disclosure section is included in an analyst report and otherwise zero. A combined disclosure section can be based on the legal basis of several different jurisdictions. Moreover, the legal basis of the combined disclosure section applied in the research report need not necessarily be mentioned. If the combined disclosure section is, among others, based on German-, US- or British law, then the indicators *Disc_German*, *Disc_USA*, *Disc_UK* also take the value of one respectively, in addition to the *Disc_Global* indicator.[77] The indicator *No_Disclosure* takes the value of one, when a research report does not include a conflicts of interest disclosure section and otherwise zero.

As can be seen in Table A2, a predominant number of the 194 analyst research reports include a conflicts of interest disclosure section. In particular, 142 out of 194 (73.2 %) analyst reports in the sample include a general combined conflicts of interest disclosure section. Moreover, only 21 out of 96 (21.9%) analyst research reports about the Swedish firm Ericsson do not include a conflicts of interest disclosure section. Thus, the results of this investigation provide evidence that capital market participants in Europe were in many cases already in-

[76] For instance, so-called "morning notes" (see e.g., Groysberg and Healy 2013; Cowen et al. 2006).
[77] Moreover, in some cases, the conflicts of interest disclosures in analyst reports are based on the legal basis of other jurisdictions (e.g., Canadian or French law). Such cases were considered as a general (*Disc_Global*) disclosure section.

formed about sell-side analysts' conflicts of interest before the MAD made disclosure of conflicts of interest compulsory for financial institutions active in EU member countries.

Table A2: Applied Regulatory Basis of Conflict of Interest Disclosure Section in the pre-MAD period

		Disc_German	**Disc_USA**	**Disc_Global**	**Disc_UK**	**No_Disclosure**
Firm Name	*No. of Reports*	*No. of Counts*	*No. of Counts*	*No. of Counts*	*No. of Counts*	*No. of Counts*
Deutsche Telekom	45	10	13	32	3	4
Siemens	53	6	10	44	2	3
Ericsson	96	5	12	66	2	21
$\sum$	194	21	35	142	7	28

Table A2 contains information about the applied regulatory basis of the conflict of interest disclosure section within the time frame after the introduction of the relevant US regulatory measures (e.g., Hovakimian and Saenyasiri 2014) and before the introduction of the MAD in the respective country. The indicators *Disc_German*, *Disc_USA*, *Disc_UK* take the value of one, when a disclosure section included in an analyst research report is based on German-, US- or British law and otherwise zero, respectively. The indicator *Disc_Global* takes the value of one when a general combined disclosure section is included in an analyst report and otherwise zero. A combined disclosure section can be based on the legal basis of several different jurisdictions. Moreover, the legal basis of the combined disclosure section applied in the research report need not necessarily be mentioned. If the combined disclosure section is based on German-, US- or British law, in addition to the *Disc_Global* indicator, also the indicators *Disc_German*, *Disc_USA*, *Disc_UK* take the value of one, respectively. Moreover, in some cases, the conflicts of interest disclosures in analyst reports were based on the legal basis of other jurisdictions (e.g., Canadian or French law). Such cases were considered as a general (*Disc_Global*) disclosure section. The indicator *No_Disclosure* takes the value of one, when a research report does not include a conflicts of interest disclosure section and otherwise zero.

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