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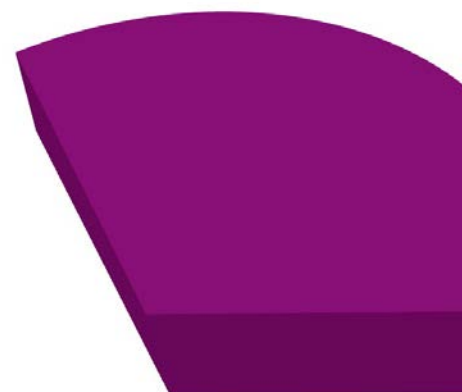
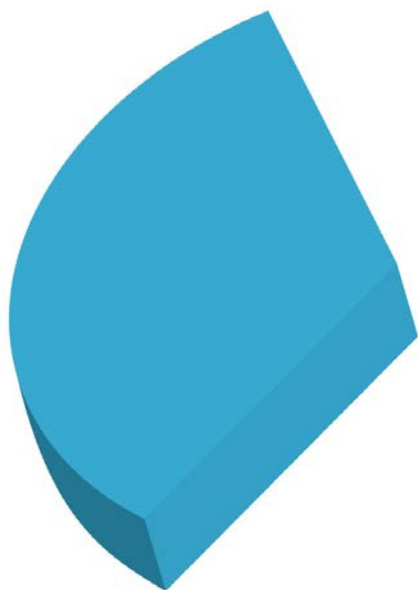
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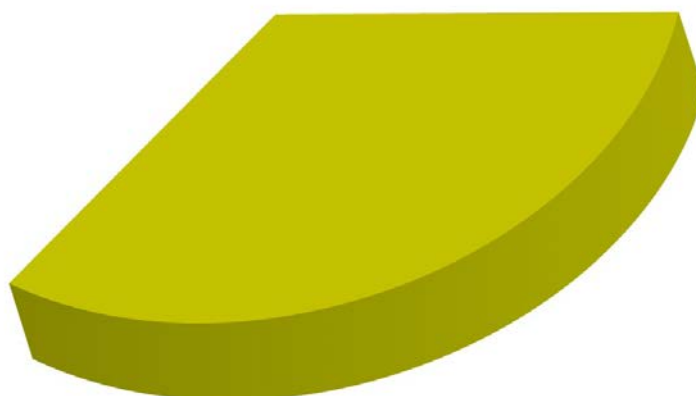
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**Optimism Bias in Financial Analysts'  
Earnings Forecasts: Do Commission-  
Sharing Agreements Reduce Conflicts  
of Interest?**

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# Optimism bias in financial analysts' earnings forecasts: Do commission-sharing agreements reduce conflicts of interest?

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## Abstract

Implemented in May 2007, the French rules governing commission-sharing agreements (CSAs) consist of unbundling brokerage and investment research fees. The goal of this paper is to analyze the effect of these rules on analysts' forecasts. Based on a sample of one-year-ahead earnings per share forecasts for 58 French firms during the period from 1999 to 2011, we conduct panel data regressions. We show that the analysts' optimistic bias declined significantly after CSA rules, which suggests that these rules are effective at curbing the conflicts of interest between brokerage activities and financial research. Our results are robust to the impact of the Global Settlement and the Market Abuse Directive.

JEL Classification : G17, G24, G28

Keywords: financial analysts, EPS forecasts, optimism, conflicts of interest, commission sharing agreements.

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# 1 Introduction

Financial analysts provide information that is critical for financial markets to function properly. By issuing investment recommendations and forecasts of share values or earnings per share (EPS), financial analysts reduce information asymmetries between firms and investors or fund managers. Generally issued on behalf of brokers (in this case, analysts are referred to as “sell-side analysts”), forecasts and recommendations are widely used by fund managers for making portfolio allocation decisions.

However, sell-side analysts’ forecasts and recommendations are excessively optimistic, which reduces the informational efficiency of financial markets.<sup>1</sup> One important source of optimism in sell-side analysts’ forecasts is the presence of conflicts of interest between research and investment banking or brokerage activities (Devos, 2014, Arand and Kerl, 2015 and Mathew and Yildirim, 2015).<sup>2</sup> First, when an analyst is linked to a financial institution that provides investment banking services to firms, issuing optimistic forecasts or recommendations for a firm allows the analyst to please his employer by helping him develop or maintain a customer relationship with the firm manager (Lin and MacNichols, 1998, Michaely and Womack, 1999, Dechow et al., 2000, Lin et al., 2005, McKnight et al., 2010). Second, conflicts of interest may also emerge when sell-side analysts are employed by brokers, who provide not only investment research but also brokerage services (Carleton et al., 1998, Jackson, 2005, Mehran and Stulz, 2007, Agrawal and Chen, 2012). In this case, analysts produce optimistic forecasts or recommendations in the hope of generating buying orders and charging brokerage fees to customers.

Recent financial reforms have attempted to curb conflicts of interest in the financial research industry (Espahbodi et al., 2015). The most widely studied regulation is the Global Settlement (GS), which was announced in the US in December, 2002. The 12 large investment banks involved in this agreement are compelled to clearly separate their financial research and investment banking activities. A great deal of empirical literature shows that the GS was effective in reducing analysts’ optimistic bias (Heflin et al., 2003, Mohanram and Sunder, 2006, Kadan et al., 2009, Clarke et al., 2011, Guan et al., 2012, Hovakimian and Saenyasiri, 2010, 2014).

Some financial reforms have also been implemented in Europe. In France, rules governing commission-sharing agreements (CSAs) were implemented by the *Autorité des Marchés Financiers* (AMF, the French Financial Markets Authority) in May 2007. In contrast to the GS, which addresses the conflicts of interest between financial research

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<sup>1</sup>A persistent optimism bias has also been observed in management forecasts by Japanese firms (Kato et al., 2009, Cho et al., 2011).

<sup>2</sup>Optimism may also arise from the analysts’ concern for satisfying firm management and ensuring their access to soft information released by managers (Francis and Philbrick, 1993, Matsumoto, 2002, Burgstahler and Eames, 2006, Green et al., 2014). By prohibiting any form of selective information release by large firms to analysts or investors, the Regulation Fair Disclosure Act, which was implemented in the US in October 2000, is intended to curb such behavior (Heflin et al., 2003, Mohanram and Sunder, 2006).

and investment banking, the aim of the rules governing CSAs is to eliminate conflicts of interest between financial research and brokerage activities. Indeed, whereas brokerage activities and financial research were previously provided as a single package and charges globally, the new regulation mandates unbundling the fees for these two types of services. Moreover, when an investor purchases brokerage services from an execution broker and financial research services from an independent analyst (i.e., an analyst who is not employed by a broker or an investment bank), the investor and the broker can enter into a CSA.<sup>3</sup> Under such an arrangement, the broker must remit the financial research portion of the commission to the independent analyst. This regulation should reduce the optimistic bias in the financial research industry for two reasons. First, it promotes independent analysis, which is less subject to conflicts of interest and, consequently, to optimistic bias. Second, the rules governing CSAs clarify the actual cost of financial analysis. Therefore, mutual fund managers should be more careful about the way forecasts are produced, which should reduce sell-side analysts' incentive to intentionally bias forecasts to generate brokerage commissions.

To the best of our knowledge, whereas earlier empirical contributions have mainly focused on the separation between financial analysis and investment banking, no investigation has been conducted to assess whether financial reforms are also effective at curbing conflicts of interest between research and brokerage activities. The goal of this paper is precisely to fill this gap. Assessing the effect of the rules governing CSAs appears all the more interesting because the unbundling of research and execution fees is also a key element of the updated Markets in Financial Instruments Directive (MiFID2), which should take effect in 2017. Therefore, addressing the effectiveness of CSAs at curbing conflicts of interest between financial research and brokerage activities may be seen as a first step in evaluating the unbundling device that will soon be applied in Europe.

By conducting panel regressions on a data set that includes I/B/E/S analysts' EPS forecasts for 58 French firms from the *Euronext 100* index from January 1999 to December 2011 on a monthly basis, we show that the policy on CSAs has mitigated the conflicts of interest faced by financial analysts and reduced their optimistic bias. This result is in that it accounts for other financial regulations, such as the GS and the Market Abuse Directive (MAD).

The paper is organized as follows. Section 2 provides the theoretical and empirical background for our research. Our methodology is presented in Section 3. Section 4 presents our results. Section 5 proposes some extensions to our work. Section 6 concludes the paper.

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<sup>3</sup>*Commission de Courtage à Facturation Partagée (CCP)* in French.

## 2 Literature

In this section, we present the framework of our study. We first focus on the sources of conflicts of interest. We then present the impact of regulations on conflicts of interest.

Optimism in financial analysts' forecasts can result from two types of conflicts of interest.

On the one hand, conflicts of interest and over-optimism may arise when the analyst is linked to (employed by) a financial institution that provides investment banking services to firms. By encouraging investors to buy newly issued securities of a firm, issuing optimistic forecasts or recommendations for a firm allows the analyst to please his employer by helping him to win or to preserve a potentially lucrative customer relationship with the firm. First, this increases the investment bank's likelihood to be selected by the firm as a lead or a co-underwriter for equity offerings. Second, once the investment bank is selected, it is able to secure the firm's underwriting activity. Relying on an I/B/E/S dataset over the period 1989-1994, Lin and MacNichols (1998) find that affiliated analysts, i.e., analysts employed by an investment bank that intervenes as a leader or co-underwriter of a firm, issue more optimistic forecasts about this firm than do non-affiliated analysts. This finding is corroborated by McKnight et al. (2010) on a large dataset covering 13 countries (Austria, Belgium, Denmark, Finland, France, Germany, Italy, the Netherlands, Norway, Spain, Sweden, Switzerland and the United Kingdom). Finally, using a sample covering the 1981-1990 period, Dechow et al. (2000) show that analysts who are employed by an investment bank that manages an IPO produce more optimistic forecasts than do others. This result also holds in the case of analysts' recommendations, as Michaely and Womack (1999) demonstrate.

On the other hand, conflicts of interest may exist when sell-side analysts are employed by brokers that provide not only financial research but also brokerage services (Jackson, 2005, Mehran and Stulz, 2007). Indeed, issuing optimistic forecasts encourages customers to buy stocks, thus allowing brokers to charge brokerage fees. It is true that pessimistic forecasts or recommendations also generate (selling) transaction fees. However in contrast to selling transactions, buying orders do not face short-selling constraints. Moreover, because buying transactions usually induce selling transactions in the future, optimism provides a double opportunity to charge brokerage commissions. Based on a sample of 2,300 analysts employed by more than 200 brokerage and non-brokerage firms in December 1994, Carleton et al. (1998) show that brokerage firms produce more optimistic recommendations than do non-brokerage firms. Similarly, using I/B/E/S data for the US between 1994 and 2003, Agrawal and Chen (2012) reveal that optimism increases with the intensity of conflicts of interest, measured by the share of the brokers' profit resulting from brokerage activity.

Some recent financial reforms have attempted to curb the conflicts of interest described above. Announced in December 2002 and officially published on April 28,

2003,<sup>4</sup> the GS is an agreement among the US Government, the SEC, the NYSE, the NASD and 12 large investment banks (Citigroup, Bear Stearns, Credit Suisse, JP Morgan, Goldman Sachs, Morgan Stanley, Merrill Lynch, UBS, Lehman Brothers and U.S. Bancorp Piper Jaffray).<sup>5</sup> The 12 banks involved in this agreement (“the 12 big banks” or “the sanctioned banks”) are compelled to implement a clear separation between financial research departments and investment banking activities and to disclose information about their financial research process and historical ratings.<sup>6</sup> Kadan et al. (2009) show that analysts’ recommendations are less likely to be optimistic (i.e., “buy” or “strong buy”) over the post-GS period (between September 2002 and December 2004) compared to the pre-GS period (from November 2000 to August 2002). Clarke et al. (2011) find that the reduction in the optimistic bias consecutively to the GS is particularly strong for affiliated analysts (who are employed by a bank having a business link with a firm). Moreover, based on a sample of 40 countries over the 1991-2010 period, Hovakimian and Saenyasiri (2014) show that the GS reduced analyst forecast bias more strongly in those countries where the 12 big banks are strongly present and those with low investor protection. In the same vein, Guan et al. (2012) reveal that recommendations issued by sanctioned banks’ analysts are significantly more optimistic in the pre-reform period than in the post-reform period. Taken together, these findings suggest some effectiveness of the GS in neutralizing analysts’ conflicts of interest.

The MAD, enacted in the European Community in 2003 and transposed into the national laws of each European country between 2004 and 2006, implements strong disclosure rules concerning the research process of financial analysts and any information that could affect forecasts or recommendations such as analysts’ remuneration schemes or institutional affiliation. Using a dataset of 15 European countries between 1997 and 2007, Dubois et al. (2014) show that the MAD significantly reduced the optimistic bias of analysts who are linked to an investment bank that has a business relationship with the firm on which the recommendation is issued. This effect is amplified in countries where the severity of sanctions in the event of violations is high.

### 3 Methodology

This section addresses our methodology by successively presenting the data used, the testable assumption of our research and the econometric model employed.

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<sup>4</sup>A first set of GS rules (New York Stock Exchange (NYSE) rule 472 and National Association of Security Dealers (NASD) rule 2711) intended to limit the links between investment banking and research activities within banks were enacted in September 2002. For a more specific investigation of the effect of NASD rule 2711 on analysts’ recommendations, see Barber et al. (2007).

<sup>5</sup>Deutsche Bank and Thomas Weisel Partners entered into the agreement on August 26, 2004.

<sup>6</sup>For example, the GS regulation forbids the analysts employed by these financial institutions from following bankers in roadshows organized by a firm that is preparing a public offering. Moreover, the IPO “quiet period” was increased from 25 days to 40 days.

### 3.1 Data

Provided by Thomson Reuters, our dataset includes I/B/E/S EPS forecasts and additional data from Worldscope. Our dataset contains 58 French firms from the *Euronext 100* index (as it was composed between January and December 2011) that were categorized according to firm size and sector. The dataset also includes firms' share prices for each month, i.e., the closing share price of the Thursday before the third Friday of every month. We study one-year-ahead EPS forecasts from January 1999 to December 2011 on a monthly basis.<sup>7</sup>

Several steps were required to clean the data. First, once issued, a forecast is frequently repeated for several months in the database. We obtained the number of monthly occurrences of each forecast. Then, we dropped repeated occurrences of the each forecast to avoid artificially counting such repeated forecasts several times. Second, the final day of the fiscal year (we used fiscal years rather than calendar years) was carefully checked. Third, we dropped aberrant observations (for example, those that occur when there are several different forecasts from the same analyst on the same day for the same firm). Because the reported forecasts are supposed to be one-year-ahead earnings forecasts, we created a variable called the "horizon," which measures the time elapsed (as a percentage of years) between the earnings announcement date and the forecast release date. We then dropped forecasts for which the "horizon" was negative or exceeded 365 days (366 for leap years). Fourth, we dropped all firm-analyst pairs that were associated with fewer than five forecasts. We also dropped all analysts covering only one firm and all firms covered by only one analyst. Finally, we were left with a sample consisting of 7,067 firm-time observations.

### 3.2 Testable assumption

The rules governing CSAs were implemented by the French Financial Markets Authority (AMF) on May 18, 2007.<sup>8</sup> Whereas brokerage and financial research were previously provided as a single package and charges covered both, investors, such as portfolio management companies, must now clearly split fees into two separate components: the brokerage fee and the investment research commission. When an investor purchases brokerage services from an execution broker and financial research services from an independent research provider, the investor and the broker can enter into a CSA. Such an arrangement stipulates that the broker must remit the portion of the fee that corresponds to financial research to the independent financial analyst. This regulation applies to French mutual funds, i.e., mutual funds that are established in France (i.e., that are approved by the AMF or the authority of another country belonging to

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<sup>7</sup>The data from I/B/E/S are provided by Thomson Financial as part of an academic program to encourage research on French stocks. The period from 1999 to 2011 allows us to measure not only the effect of the rules governing CSAs but also the impact of the GS and the MAD (see Section 5).

<sup>8</sup>The device is detailed in Article 317-79 et seq. of the General Regulation of the AMF and the AMF's instruction # 2007-02.



the European Economic Area) and governed by French law, which are denoted below by “French mutual funds.”

In accordance with the literature on the conflicts of interest between brokerage and investment research, the rules governing CSAs should reduce analysts’ optimism in two ways. First, they facilitate investors’ access to independent financial analysts, who do not deliver execution services and, for this reason, are less subject to conflicts of interest and optimistic bias (Carleton et al., 1998, Jackson, 2005, Mehran and Stulz, 2007 and Agrawal and Chen, 2012). Second, by splitting the fees into brokerage fees and investment research commissions, the rules governing CSAs improve transparency and clarity about the actual cost of financial analysis. For this reason, mutual fund managers should be more careful about the way forecasts are produced, which should mitigate sell-side analysts’ incentive to intentionally bias forecasts to generate brokerage commissions. Therefore, we have the following testable assumption:

*H1: The implementation of rules governing CSAs reduces optimism bias in analyst forecasts.*

Our dataset does not provide any information on whether analysts have signed a CSA with a portfolio management company. However, there are good reasons to think that using a dataset based on French firms is the most suitable way to capture the impact of the AMF regulation on analysts’ behavior. Indeed, as mentioned above, only French mutual funds can enter into a CSA. Therefore, if the rules governing CSAs are effective at mitigating conflicts of interest, they should particularly reduce optimistic bias in the case of firms for which French mutual funds purchase investment research, i.e., for firms whose stocks are held by French mutual funds. It turns out that these firms are mainly French firms. For example, at the end of 2014, French stocks represented 43.8% of the stocks owned by French non-monetary mutual funds, compared to 30.2% for other Euro Area stocks and 26% for stocks from the rest of the world (Fourel and Potier, 2015). Similarly, at the end of March 2013, the number of French listed stocks owned by French portfolio management companies comprised a large proportion of the French stocks listed in financial markets. In 2011, they owned approximately 20% of the CAC40 and SBF250 indexes’ capitalization and 25% of the CAC small index capitalization (Paris Europlace, 2013). This proportion is quite stable over time.

As a consequence, if the rules governing CSAs are effective at reducing optimism among financial analysts, this effect should be particularly apparent in EPS forecasts for French firms.

### **3.3 Econometric model**

As mentioned above, the rules governing CSAs should reduce analysts’ optimism in two ways: by promoting independent analysis and by curbing the conflicts of interest

faced by sell-side analysts. For this reason, we expect a reduction in analyst optimism following the imposition of the rules governing CSAs.<sup>9</sup>

Therefore, to assess our testable assumption, H1, we estimate the following model:

$$\begin{aligned} OPTIM_{i,t} = & \alpha + \beta_1 CSA + \beta_2 GROWTH_t + \beta_3 EPSNEGATIVE_{i,t} & (1) \\ & + \beta_4 EPSDECLINE_{i,t} + \beta_5 MONTH_t + \beta_6 COVER_{i,t} \\ & + \beta_7 SIZE_{i,t} + \beta_8 DISP_{i,t} + \beta_9 LEVERAGE_{i,t} + \beta_{10} MTB_{i,t} + \epsilon \end{aligned}$$

Following Hovakimian and Saenyasiri (2010, 2014), the dependent variable, denoted  $OPTIM_{i,t}$ , measures the optimism of the analysts' forecast consensus,

$$OPTIM_{i,t} = 100(F_{i,t} - A_{i,t})/P_{i,t}, \quad (2)$$

where

$$F_{i,t} = \frac{\sum_j F_{i,j,t}}{N_j}. \quad (3)$$

$F_{i,j,t}$  is the EPS forecast for firm  $i$  by analyst  $j$  on date  $t$ ,  $N_j$  is the number of analysts,  $A_{i,t}$  is the actual value of firm  $i$ 's EPS that was forecast on date  $t$ , and  $P_{i,t}$  is the stock price of firm  $i$  on date  $t$ .<sup>10</sup> Therefore,  $F_{i,t}$  measures the analysts' consensus on firm  $i$  in month  $t$ . Then, to reduce the effects of outliers on the ratio's distribution, we winsorized  $OPTIM_{i,t}$  at 10% by setting all the data below the 5th percentile equal to the 5th percentile and setting the data above the 95th percentile equal to the 95th percentile.  $CSA$  is a dummy variable that equals 1 if the consensus forecast was produced after the enactment of rules governing CSAs (i.e., after May 18, 2007) and 0 if it was produced before that date (i.e., before May 18, 2007). In accordance with H1,  $\beta_1$  should be significantly negative.

The rules for CSAs were implemented in 2007 during the financial crisis. In bad times, analysts are expected to be more optimistic to encourage customers to buy stocks despite low economic growth. Conversely, when macroeconomic conditions improve, it is less necessary to inflate EPS forecasts (Kadan et al., 2009, Hovakimian and Saenyasiri, 2010, 2014). Therefore, we ensure that the effect of  $CSA$  cannot be attributed to poor macroeconomic conditions by controlling for the quarterly growth

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<sup>9</sup>Using financial press releases and the websites of analysts' employers, we were able to classify analysts as "independent" (i.e., employed neither by a broker nor by an investment bank) and "dependent" (i.e., employed by a broker and/or an investment bank). The number of independent research providers in our dataset increased significantly (from 4 to 11, of which more than half are Anglo-Saxon) after the policy on CSAs was implemented. However, because our sample nearly entirely consists of forecasts issued by dependent analysts (they represent 98.8% of all observations), it is not possible to estimate a difference-in-difference model to examine whether they have been more strongly affected by CSA rules than have independent analysts.

<sup>10</sup>Prior research usually uses the share price or the EPS as a measure of scale. However, the stock price is often preferred to the EPS because earnings can be negative (Heflin et al., 2003, Mohanram and Sunder, 2006, Herrmann et al., 2008, Richardson et al., 2004).

rate of the GDP in the  $t$  quarter, which is denoted by  $GROWTH_t$ . The sign of  $\beta_2$  is expected to be negative.

We also intend to capture the effect of the financial crisis at the firm level. Analysts are more prone to issuing optimistic forecasts about firms with negative earnings. Following Duru and Reeb (2002), Heflin et al. (2003), Herrmann et al. (2008), Coen et al. (2009) and Hovakimian and Saenyasiri (2010), we construct two dummy variables.  $EPSNEGATIVE_{i,t}$  equals 1 if the actual earnings of firm  $i$  at  $t$  are negative and 0 otherwise.  $EPSDECLINE_{i,t}$  equals 1 if the actual earnings of firm  $i$  at  $t$  declined compared to the earnings at  $t - 1$  and 0 otherwise. These variables are both expected to have positive impacts on the dependent variable. Therefore, the  $\beta_3$  and  $\beta_4$  are expected to have positive signs.

Moreover, we investigate the seasonal dimension of forecast activity. As emphasized by Libby et al. (2008) and Richardson et al. (2004), analysts are more prone to producing optimistic forecasts at the beginning of the fiscal year (to make firm securities more attractive), and they are more inclined to issue pessimistic forecasts at the end of the fiscal year (to avoid negative earnings surprises on the announcement date). To test for the existence of this “walkdown to beatable forecasts behavior,”<sup>11</sup> we introduce the variable  $MONTH_t$ , which varies from 1 (for January) to 12 (for December). Because analysts should be more optimistic in January than in December, the sign of  $\beta_5$  is expected to be negative.

We also capture stocks’ information environment. In accordance with Lim (2001) and Das et al. (1998), analysts are incentivized to inflate their forecasts to maintain friendly relationships with firm management and to have access to the information that managers selectively disclose. This behavior is likely to be stronger for firms that are more complex and have less publicly available information. We include several variables in the regression to account for these characteristics. First, because the availability of public information is enhanced for large firms and firms that are followed by a large number of analysts, we introduce the variables  $COVER_{i,t}$ , which is the number of analysts who follow firm  $i$  at  $t$  (Duru and Reeb, 2002, Herman et al., 2008, Hovakimian and Saenyasiri, 2010, Dubois et al., 2014) and  $SIZE_{i,t}$ , the log of firm  $i$ ’s market capitalization at  $t$  (Duru and Reeb, 2002, Herman et al., 2008, Hovakimian and Saenyasiri, 2010). The signs of  $\beta_6$  and  $\beta_7$  are expected to be negative. Second, the dispersion of analysts’ forecasts, denoted by  $DISP_{i,t}$  and measured as the standard deviation of analysts’ forecasts for firm  $i$  at  $t$ , also reflects the difficulty of forecasting firm  $i$ ’s EPS (Diether et al., 2002, Duru and Reeb, 2002, Herrmann et al., 2008). Therefore, the expected sign of  $\beta_8$  is positive. Third, we consider  $LEVERAGE_{i,t}$ , the long-term debt divided by the book value of the equity of firm  $i$  at  $t$ . As underlined by Kwon (2002), because the EPS of a highly leveraged firm depends on many complex factors (such as the rate of inflation, the cost of capital, and future cash flow), they are

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<sup>11</sup>The concern for consistently meeting or beating analysts’ forecasts also provides an incentive for firm managers to manipulate the information they release by issuing “bad news” management forecasts (Kross et al., 2011).

particularly difficult to forecast. Therefore, the sign of  $\beta_9$  is expected to be positive. On the contrary, information on firms with strong growth opportunities is more readily available. Therefore, we include  $MTB_{i,t}$ , the market value of the total assets of firm  $i$  at  $t$  divided by the book value of the total assets. The sign of  $\beta_{10}$  is expected to be negative (Hovakimian and Saenyasiri, 2010, Guan et al., 2012).

Table 1 (in the Appendix) lists the regression variables and describes how they are computed.

## 4 Results

In this section, we report our findings. We present univariate and multivariate results successively.

### 4.1 Univariate results

Tables 2 and 3 (in the Appendix) report summary statistics and correlation coefficients, respectively. Note that *EPSDECLINE* cannot be computed for the first month of the dataset, which reduces the number of observations. Similarly, *DISP*, *LEVERAGE* and *MTB* are not available for all the firms in the sample.

Panels B and C in Table 2 indicate that in contrast with H1, *OPTIM* is, on average, higher after the enactment of rules governing CSAs. This may be because the rules governing CSAs were implemented at the beginning of the financial crisis of 2007-2008. Indeed, we observe that the mean of *GROWTH* is significantly lower in the post-CSA period than it is in the pre-CSA period. Moreover, Table 3 reports that the correlation coefficient between *CSA* and *GROWTH* is negative and significant at the 1% level. Similarly, *EPSNEGATIVE* and *EPSDECLINE* are, on average, significantly larger in the post-CSA period than in the pre-CSA period. These observations provide some support for the idea that analysts are more optimistic in bad times and for firms in difficulty. This may explain why they became more optimistic after the implementation of the policy governing CSAs. Finally, the univariate results underline the importance of controlling for the impact of the financial crisis at both firm and macroscopic levels.

### 4.2 Multivariate results

Before turning to regressions, we conduct the Philipps-Perron (PP) and Augmented Dickey Fuller (ADF) tests to check the stationarity of the variables presented above. Our results (available upon request) indicate that all of them can be assumed to be stationary.<sup>12</sup>

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<sup>12</sup>*EPSNEGATIVE* is not stationary according to the PP test but is according to the ADF test.

Table 4 reports the results of panel estimations of our model for variants [1] to [6].<sup>13</sup>

In addition to the control variables mentioned in Table 1, variants [1] to [6] include sector effects and firm-year fixed effects (Hermann et al., 2008).<sup>14</sup> In all the variants, the Hausman test  $\chi^2$  statistics reported in Table 4 indicate that a fixed-effect model is more appropriate than a random-effect model.

First, all variants in Table 4 provide very similar results regarding the signs and significance of the coefficients. This suggests that our results are quite robust.<sup>15</sup>

The results reported in Table 4 (variants [1]-[6]) indicate that the coefficient of *GROWTH* is significant and negative. This result is consistent with the view that when macroeconomic conditions are favorable, it is less necessary for analysts to issue optimistic forecasts (Hovakimian and Saenyasiri, 2010, 2014).

Turning to *EPSNEGATIVE* and *EPSDECLINE*, our results show that both variables have positive (and significant) impacts on the dependent variable. Therefore, in accordance with Duru and Reeb (2002), Herrmann et al. (2008), Coen et al. (2009) and Hovakimian and Saenyasiri (2010), analysts are more optimistic when firms are in trouble. As found by Hovakimian and Saenyasiri (2010, 2014), the coefficient of *MONTH* is significant and negative in all variants. This provides some empirical support for the existence of a “walk trend” (Libby et al., 2008 and Richardson et al., 2004): analysts are more prone to issuing optimistic forecasts at the beginning of the fiscal year than at the end.

The results reported in Table 4 also indicate that the coefficient of *COVER* is significant and positive. Although unexpected, this finding is in accordance with Carleton et al. (1998), which suggests that the tendency to issue optimistic forecasts to win lucrative customer relationships with a firm or to generate brokerage business is exacerbated when competition among analysts is strong.

As in previous theoretical and empirical contributions (Das et al., 1998, Lim, 2001 and Hovakimian and Saenyasiri, 2010), variants [1], [3] and [4] report that the coefficient of *SIZE* is significantly negative. However, in accordance with Guan et al. (2012) and Dubois et al. (2014), variant [2] yields an insignificant coefficient on *SIZE*.

The coefficient of *LEVERAGE* is significant and positive (in variants [1], [2], [4] and [5]). This is consistent with the idea that the EPS of a highly leveraged firm is particularly difficult to forecast (Kwon, 2002), which encourages analyst to maintain friendly relationships with firm managers by issuing optimistic forecasts (Lim, 2001,

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<sup>13</sup>Because our model raises the usual question of regulation endogeneity, we performed the Nakamura test to check the endogeneity of *CSA*. We first regressed *CSA* on an instrument and all other regressors of model (1). Then, we checked the validity of the instruments using Hansen’s overidentification test. Finally, we included the residuals of the first regression as an additional explanatory variable in model (1). Our results, available upon request, indicate that the coefficient for the residuals is not significant, which suggests that *CSA* is exogenous.

<sup>14</sup>There are 11 sectors: finance, health care, consumer non-durable, consumer durable, consumer services, energy, transportation, technology, basic industries, capital goods, and public utilities.

<sup>15</sup>Using the ADF and Phillips-Peron tests, we also found that the error term is stationary in all variants of model (1).

Das et al., 1998).

Finally, the coefficients of *DISP* and *MTB* are not significant, with the latter being in accordance with Richardson et al., 2004.

More importantly, in all variants, the coefficient of the variable of interest, *CSA*, is significantly negative. For example, in variant [1], which has the largest within the  $R^2$  value, the coefficient of *CSA* is significant at the 5% level, which reveals that *OPTIMISM* decreased by 0.32 after the enactment of the rules governing CSAs. Considering the mean value of *OPTIMISM* reported in Table 2 (Panel A), i.e., 0.76, the magnitude of this impact is quite large. This result provides some support for H1 and suggests that the rules governing French CSAs have decreased the optimistic bias of financial analysts. On the one hand, the rules governing CSAs have promoted independent financial research, which is less subject to conflicts of interest and, consequently, to optimistic bias. On the other hand, by clarifying the actual cost of investment research, the rules governing CSAs have also made mutual fund managers more demanding about the quality of investment research, which reduces sell-side analysts' incentive to intentionally bias their forecasts with to generate brokerage commissions.

Finally, in accordance with Kadan et al. (2009), Clarke et al. (2011), Guan et al. (2012) and Hovakimian and Saenyasiri (2010, 2014), our findings suggest that financial regulation has a sizable impact on research analysts' behavior. Whereas the empirical literature has mainly addressed conflicts of interest between financial research and investment banking, our paper indicates that financial reforms can also be effective at curbing conflicts of interest between financial research and brokerage activities.

## 5 Extensions

In this section, we consider some extensions to our work. We first check the robustness of our results by modifying the definition of consensus. We then investigate the impact of the MAD and the GS.

### 5.1 Modifying the definition of optimism

The variants in Section 4 suggest that our findings are robust to the specification of the estimation model. In this section, we perform an additional robustness check by modifying the definition of optimism. Expressions (2) and (3) become

$$OPTIM_{i,[t-1;t]} = 100(F_{i,[t-1;t]} - A_{i,t})/P_{i,t},$$

where

$$F_{i,[t-1;t]} = \frac{\sum_j (F_{i,j,t-1} + F_{i,j,t})}{N_j}.$$

In this specification,  $F_{i,[t-1;t]}$  measures the analysts' consensus on firm  $i$  using forecasts over the period  $[t-1;t]$  rather than at  $t$ . Because this variable cannot be computed for the first month of the dataset, it reduces the number of observations.

The results for variants [1]-[6] are reported in Table 5. The coefficients of the control variables have the same signs and the same significance levels as they do in Section 4, except the coefficient of *MONTH*, which is not significant. This finding suggests that using a "smoothed" measure of optimism reduces the impact of whether the forecast is issued at the beginning or the end of the fiscal year. More importantly, the coefficient of *CSA* is still negative and significant at the 5% level. Therefore, modifying the definition of optimism does not qualitatively change our main findings.

## 5.2 The impact of the MAD

In this section, we check whether the impact of the rules governing CSAs is robust to the effect of the MAD, which imposed a separation between research and investment banking activities and more transparency about the links between both activities. Because it aims to mitigate conflicts of interest between research and investment banking, the MAD should reduce analysts' optimism (Dubois et al., 2014). The goal of this section is to assess this assumption. Therefore, we build a variable, *MAD*, that equals 1 if the consensus forecast is issued after the adoption of the MAD (i.e., after December 23, 2003) and 0 if it is issued before the adoption of the MAD (i.e., before December 23, 2003). *MAD* is included as an additional dependent variable in (1) as follows:

$$\begin{aligned} OPTIM_{i,t} = & \alpha + \beta_1 CSA + \beta_2 MAD + \beta_3 GROWTH_t + \beta_4 EPSNEGATIVE_{i,t} \\ & + \beta_5 EPSDECLINE_{i,t} + \beta_6 MONTH_t + \beta_7 COVER_{i,t} \\ & + \beta_8 SIZE_{i,t} + \beta_9 DISP_{i,t} + \beta_{10} LEVERAGE_{i,t} + \beta_{11} MTB_{i,t} + \epsilon. \end{aligned} \quad (4)$$

The sign of  $\beta_2$  is expected to be negative.

Tables 6 and 7 (in the Appendix) provide summary statistics and correlation coefficients for *MAD*. The regression results are provided in Table 8.

The statistics reported in Table 6 show that *GROWTH* is, on average, lower in the post-MAD period (Panel C) than it is in the pre-MAD period (Panel B), which is corroborated by the negative correlation between *MAD* and *GROWTH* (Table 7).<sup>16</sup> Because optimistic bias is expected to decrease with *GROWTH*, this may explain why the mean value of *OPTIM* is higher during the post-MAD period (Panels B and C of Table 6). These observations provide further evidence for the need to account for the effect of economic conditions in our regression.

The results reported in Table 8 indicate that the coefficients of *GROWTH*, *EPSNEGATIVE*, *EPSDECLINE*, *MONTH*, *SIZE* and *LEVERAGE* are significant and have the

<sup>16</sup>However, in contrast with what we observed in Section 4.1, the mean of *EPSNEGATIVE* (*EPSDECLINE*) is not significantly different (lower) in the post-MAD period than it is in the pre-MAD period (Panels B and C of Table 6), and the correlations between *GS* and *EPSNEGATIVE* and between *MAD* and *EPSDECLINE* are null (Table 7).

expected signs. The coefficient of *MAD* is not significant. This indicates that the optimistic bias in the forecasts for French firms did not decrease after the MAD. This finding is in accordance with Hovakimian and Saenyasiri (2014) and Dubois et al. (2014); the latter shows that the MAD reduced optimism, but only in forecasts issued by affiliated analysts (i.e., analysts employed by a bank that has a business relationship with the firm about which the recommendation is issued).

Finally, note that the coefficient for *CSA* is still significant and negative, which suggests that our previous results concerning the impact of the rules governing CSAs are robust.

### 5.3 The international impact of the GS

As emphasized by Hovakimian and Saenyasiri (2014), because the 12 banks involved in the GS engage in international activity, this regulation may affect analysts' forecasts not only in the US but also abroad. Indeed, financial research at large investment banks is often conducted by groups of analysts covering many different countries. Moreover, the NASD requires that the foreign associates of its members also comply with the rules of the GS.

Because our dataset contains forecasts issued by analysts employed by the 12 largest banks,<sup>17</sup> we should observe a reduction in the optimistic bias after the announcement of the GS.

In accordance with Hovakimian and Saenyasiri (2010, 2014), we construct a variable, *GS*, that equals 1 if the consensus forecast is issued after the announcement of the GS (i.e., after December 20, 2002) and 0 if it is issued beforehand (i.e., before December 20, 2002). *GS* is included as an additional dependent variable in (1) as follows:

$$\begin{aligned} OPTIM_{i,t} = & \alpha + \beta_1 CSA + \beta_2 GS + \beta_3 GROWTH_t + \beta_4 EPSNEGATIVE_{i,t} + \beta_5 EPSDECLINE_{i,t} \\ & + \beta_6 MONTH_t + \beta_7 COVER_{i,t} \\ & + \beta_8 SIZE_{i,t} + \beta_9 DISP_{i,t} + \beta_{10} LEVERAGE_{i,t} + \beta_{11} MTB_{i,t} + \epsilon. \end{aligned} \quad (5)$$

The sign of  $\beta_2$  is expected to be negative.

Summary statistics and correlation coefficients for *GS* are reported in Tables 9 and 10 (in the Appendix). They exhibit the features reported for *MAD* (Tables 6 and 7).

The estimation results are provided in Table 11. Except in variant [2] (where the sign of the coefficient of *LEVERAGE* is negative and significant at the 5% level), the coefficients of *GROWTH*, *EPSNEGATIVE*, *EPSDECLINE*, *MONTH* and *SIZE* are significant and have the expected signs.

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<sup>17</sup>Among the 58,984 forecasts,  $F_{i,j,t}$ , that allowed us to calculate  $OPTIM_{i,t}$ , 210 were issued by an analyst employed by Bear Stearns, 2,170 by Deutsche Bank, 1,972 by Goldman Sachs, 1,805 by JP Morgan, 1,009 by Lehman Brothers, 227 by Merrill Lynch, 1,857 by Morgan Stanley and 2,506 by UBS.



The coefficient of  $GS$  is insignificant, which suggests that the  $GS$  has no impact on French firms' EPS forecasts. This finding may be because only a small proportion of the forecasts of our dataset are issued by analysts who are employed by the 12 largest banks. It can also be interpreted in light of Hovakimian and Saenyasiri (2014), who find that the impact of the  $GS$  on analysts' optimism is weaker in countries with low investor protection. That the French "civil law" system is usually considered a weak legal system (La Porta et al., 1997) may explain why the  $GS$  has no effect on French firms' EPS forecasts.

Finally, as in Section 5.2, the sign and the significance of the coefficient of  $CSA$  are not affected by the introduction of  $GS$  into the estimate, which provides further evidence that the results obtained in Section 4 are robust.

## 6 Conclusion

The goal of this paper was to examine whether the rules governing CSAs reduced the optimism in analysts' forecasts. Based on an I/B/E/S dataset of EPS forecasts issued for 58 French firms during the period from 1999 to 2011, we showed that the optimistic bias declined significantly after the introduction of the rules governing CSAs, even when the impacts of the  $GS$  and the  $MAD$  were accounted for. Whereas earlier empirical contributions have addressed conflicts of interest between financial research and investment banking, our paper indicates that financial regulation can also have some effectiveness in curbing the conflicts of interest between financial research and brokerage activities.

On the one hand, the rules governing CSAs have increased mutual fund managers' access to independent financial analysts, who are less subject to conflicts of interest and, consequently, to optimistic bias. On the other hand, they have also improved clarity about the actual cost of investment research, which has made mutual fund managers more demanding about the quality of research. For this reason, they have reduced sell-side analysts' incentives to intentionally bias their forecasts to generate brokerage activity.

Our findings have several implications. First, the rules governing CSAs may have increased informational and allocative efficiency in financial markets and thereby, improved fund managers' portfolio allocations. However, they may also have affected the business models and pricing policies of brokers and independent financial analysts. For example, if brokers have balanced the impact of fiercer competition on investment research services by increasing brokerage commissions, they may have increased fund managers' costs and thereby, made the global impact of the rules governing CSAs on funds' performance and investors' utility quite ambiguous.

Second, by making financial information more reliable, the rules governing CSAs may have also facilitated firms' access to financial markets, especially those for which financial information is not readily available. This conclusion appears particularly

interesting at a time when the French regulator and other players in the financial industry seek to promote the coverage of small firms by analysts, especially when they go public.

Finally, our results also have regulatory implications. Because they address the unbundling of research and execution fees, which is a key element of the MiFID2, our findings have a forward-looking dimension. It is not yet very clear how research payment accounts (RPAs, i.e., accounts operated by asset managers and specifically, dedicated to paying for external investment research), which are provided by the MiFID2, will be implemented in practice. But our paper notes the need for in-depth reflection about the way in which CSAs and RPAs should co-exist to make the unbundling device as effective as possible.

Our results undoubtedly call for further research. First, it would be interesting to collect precise information on the CSAs entered into by the brokers in our dataset to determine whether signing a CSA (or the number of CSAs) reduces financial analysts' optimistic bias. More ambitiously and in the longer term, our work could be also extended by a wider analysis of the implications of the MiFID2 for the European investment research industry.

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# Appendix

Table 1: List of regression variables

<b>DEPENDENT VARIABLE</b>	
<i>OPTIM</i>	Winsorized ratio defined as the difference between the EPS forecast consensus on firm $i$ at date $t$ and the actual firm $i$ 's EPS that was forecasted at date $t$ , divided by the firm $i$ 's stock price at $t$ .
<b>EXPLANATORY VARIABLES AND EXPECTED SIGNS</b>	
<i>CSA</i> (-)	Dummy variable that equals 1 if the consensus forecast is issued after CSA rules (i.e., after 18, May 2007) and 0 before (i.e., before 18, May 2007).
<i>GROWTH</i> (-)	Quarterly growth rate of real GDP in France on the quarter of month $t$ .
<i>EPSNEGATIVE</i> (+)	Dummy variable that equals 1 if the firm $i$ 's EPS is negative at $t$ and 0 otherwise.
<i>EPSDECLINE</i> (+)	Dummy variable that equals 1 if the firm $i$ 's EPS declined at $t$ compared to $t - 1$ , and 0 otherwise.
<i>MONTH</i> (-)	Variable that varies from 1 to 12 for each month of the year.
<i>COVER</i> (-)	Coverage of the firm $i$ at $t$ (number of analysts who follow firm $i$ at $t$ ).
<i>SIZE</i> (-)	Size of the firm $i$ at $t$ (log of market capitalization of firm $i$ at $t$ ).
<i>DISP</i> (+)	Standard deviation of analysts' forecasts on firm $i$ at $t$ .
<i>LEVERAGE</i> (+)	Long-term debt divided by the book value of equity of firm $i$ at $t$ .
<i>MTB</i> (-)	Market value of total asset divided by the book value of total asset of firm $i$ at $t$ .

Table 2: Statistical summary for regression variables (1997-2011)

<b>PANEL A: Whole period</b>					
% of optimistic forecasts: 47					
Variable	Nb. obs.	Mean	Standard deviation	Min	Max
<i>OPTIM</i>	7,067	0.63	3.10	-3.58	10.26
<i>CSA</i>	7,067	0.35	0.47	0	1
<i>GROWTH</i>	7,067	0.35	0.58	-1.62	1.20
<i>EPSNEGATIVE</i>	7,067	0.07	0.26	0	1
<i>EPSDECLINE</i>	6,540	0.34	0.47	0	1
<i>MONTH</i>	7,067	6.49	3.44	1	12
<i>COVER</i>	7,067	21.54	8.69	1	48
<i>SIZE</i>	7,067	9.20	1.12	5.48	12.12
<i>DISP</i>	6,728	0.68	1.29	0	22.46
<i>LEVERAGE</i>	6,908	362.10	208.77	1	738
<i>MTB</i>	6,952	0.84	1.11	0	17.86

<b>PANEL B: Pre-CSA period</b>					
% of optimistic forecasts: 43					
Variables	Nb. obs.	Mean	Standard deviation	Min	Max
<i>OPTIM</i>	4,583	0.26	2.80	-3.58	10.26
<i>GROWTH</i>	4,583	0.55	0.36	-0.18	1.20
<i>EPSNEGATIVE</i>	4,583	0.06	0.23	0	1
<i>EPSDECLINE</i>	4,056	0.26	0.44	0	1
<i>MONTH</i>	4,583	6.32	3.46	1	12
<i>COVER</i>	4,583	21.76	9.13	1	48
<i>SIZE</i>	4,583	9.14	1.17	5.48	12.12
<i>DISP</i>	4,358	0.65	1.16	0	19.57
<i>LEVERAGE</i>	4,537	367.74	204.37	1	738
<i>MTB</i>	4,514	0.91	1.25	0.08	17.86

<b>PANEL C: Post-CSA period</b>					
% of optimistic forecasts: 54					
Variables	Nb. obs.	Mean	Standard deviation	Min	Max
<i>OPTIM</i>	2,484	1.31 <sup>+++</sup>	3.50	-3.58	10.26
<i>GROWTH</i>	2,484	0.02 <sup>---</sup>	0.73	-1.61	1.07
<i>EPSNEGATIVE</i>	2,484	0.10 <sup>+++</sup>	0.30	0	1
<i>EPSDECLINE</i>	2,484	0.46 <sup>+++</sup>	0.49	0	1
<i>MONTH</i>	2,484	6.81 <sup>+++</sup>	3.37	1	12
<i>COVER</i>	2,484	21.14 <sup>---</sup>	7.80	1	40
<i>SIZE</i>	2,484	9.32 <sup>+++</sup>	1	6.08	11.92
<i>DISP</i>	2,370	0.74 <sup>+++</sup>	1.49	0	22.46
<i>LEVERAGE</i>	2,371	351.32 <sup>---</sup>	216.57	5	734
<i>MTB</i>	2,438	0.69 <sup>---</sup>	0.75	0	6.45

<sup>+++</sup> indicates that the mean of the variable in the post-CSA period is significantly higher than in the pre-CSA period at the 1% level.

<sup>---</sup> indicates that the mean of the variable in the post-CSA period is significantly weaker than in the pre-CSA period at the 1% level.

Table 3: Correlation coefficients of regression variables (1999-2011)

	<i>OPTIM</i>	<i>CSA</i>	<i>GROWTH</i>	<i>EPSNEGATIVE</i>	<i>EPSDECLINE</i>	<i>MONTH</i>	<i>COVER</i>	<i>SIZE</i>	<i>DISP</i>	<i>LEVERAGE</i>	<i>MTB</i>
<i>OPTIM</i>	1										
<i>CSA</i>	0.1620***	1									
<i>GROWTH</i>	-0.2047***	-0.4287***	1								
<i>EPSDECLINE</i>	0.6726***	0.0847***	-0.0973***	1							
<i>EPSNEGATIVE</i>	0.4559***	0.2020***	-0.2585***	0.2639***	1						
<i>MONTH</i>	0.0039	0.0683***	0.0206	0.0021	0.0431***	1					
<i>COVER</i>	0.0845***	-0.0338***	0.0544***	0.0386***	-0.0082	0.4078***	1				
<i>SIZE</i>	-0.0085	0.0738***	0.0361***	-0.0967***	0.1011***	-0.0063	0.5823***	1			
<i>DISP</i>	0.0855***	0.0311	-0.0162	0.1402***	0.0051	-0.0004	0.0387***	0.0225	1		
<i>LEVERAGE</i>	0.0224	-0.0373***	-0.0228	-0.0517***	0.0051	0.0004	-0.0021	-0.0081	0.0176	1	
<i>MTB</i>	-0.0944***	-0.0971	0.0907***	-0.1162***	-0.1537***	0.0115	-0.0234***	0.0907***	0.1057***	-0.2336***	1

\*\*\* denotes significance at the 1% level.



Table 4: Results of panel (fixed-effect) regressions (1999-2011)

Variables (expected sign)	[1]	[2]	[3]	[4]	[5]	[6]
<i>CSA</i> (-)	-0.3236** (0.1476)	-0.3223** (0.1455)	-0.3187** (0.1456)	-0.2940** (0.1417)	-0.3449** (0.1486)	-0.2963** (0.1391)
<i>GROWTH</i> (-)	-0.3090*** (0.0806)	-0.3200*** (0.0728)	-0.3118*** (0.0718)	-0.3054*** (0.1704)	-0.3779*** (0.0771)	-0.3450*** (0.0706)
<i>EPSNEGATIVE</i> (+)	6.8321*** (0.6914)	6.8477*** (0.6954)	6.9020*** (0.6815)	6.6533*** (0.7716)	6.8632*** (0.7112)	6.7859*** (0.7713)
<i>EPSDECLINE</i> (+)	1.9710*** (0.2442)	1.9481*** (0.2421)	1.9515*** (0.2429)	2.0023*** (0.2448)	1.9781*** (0.2456)	1.9519*** (0.2424)
<i>MONTH</i> (-)	-0.0243** (0.0116)	-0.0223** (0.0114)	-0.0248*** (0.0114)	-0.0227** (0.0117)	-0.0255** (0.0115)	-0.0216** (0.0110)
<i>COVER</i> (-)	0.0335*** (0.0087)	0.0323*** (0.0086)	.0340*** (0.0084)	.0334*** (0.0089)	0.0341*** (0.0085)	0.0328*** (0.0086)
<i>SIZE</i> (-)	-0.4887** (0.2720)	-0.2704 (0.2059)	-0.4520** (0.2705)	-0.4508** (0.2664)		
<i>DISP</i> (+)	0.0073 (0.0693)	0.0090 (0.0687)	0.0054 (0.0696)		0.0086 (0.0690)	
<i>LEVERAGE</i> (+)	0.0082*** (0.0135)	0.0062*** (0.0001)		0.0082*** (0.0013)	0.0065*** (0.0008)	
<i>MTB</i> (-)	0.2705 (0.1787)		0.2569 (0.1760)	0.2781 (0.1771)	0.0720 (0.1161)	
Firm-year effects	yes	yes	yes	yes	yes	yes
Sector effects	yes	yes	yes	yes	yes	yes
Nb. obs.	6,005	6,096	6,023	6,301	6,005	6,540
$R^2$ within	0.8338	0.8329	0.8334	0.8241	0.8335	0.8228
Hausman test $\chi^2$	597.90	622.29	622.47	685.86	524.83	779.25
Prob> $\chi^2$	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001

All estimations are corrected for heteroskedasticity.

\*\* and \*\*\* denote significance at the 5% and 1% levels, respectively.

Table 5: Results of panel (fixed-effect) regressions with  $OPTIM_{i,[t-1;t]}$  (1999-2011)

Variables (expected sign)	[1]	[2]	[3]	[4]	[5]	[6]
<i>CSA</i> (-)	-0.3762** (0.1575)	-0.3750** (0.1551)	-0.3661** (0.1552)	-0.3332** (0.1496)	-0.4043** (0.1590)	-0.3403** (0.1467)
<i>GROWTH</i> (-)	-0.3122*** (0.0690)	-0.3240*** (0.0684)	-0.3064*** (0.0670)	-0.3072*** (0.0654)	-0.4078*** (0.0779)	-0.3834*** (0.0700)
<i>EPSNEGATIVE</i> (+)	7.1064*** (0.7497)	7.1254*** (0.7526)	7.1664*** (0.7367)	7.0601*** (0.8109)	7.1511*** (0.7723)	7.1888*** (0.8094)
<i>EPSDECLINE</i> (+)	1.9446*** (0.2401)	1.9211*** (0.2387)	1.9354*** (0.2389)	1.9594*** (0.2436)	1.9551*** (0.2430)	1.9255*** (0.2430)
<i>MONTH</i> (-)	-0.01867 (0.0125)	-0.0170 (0.0121)	-0.0186 (0.0122)	-0.0179 (0.0118)	-0.0203 (0.0125)	-0.0182 (0.0112)
<i>COVER</i> (-)	0.0311*** (0.0100)	0.0301*** (0.0098)	0.0312*** (0.0099)	0.0301*** (0.0100)	0.0322*** (0.0098)	0.0303*** (0.0096)
<i>SIZE</i> (-)	-0.6806** (0.3291)	-0.4413* (0.2425)	-0.6618** (0.3265)	-0.6637*** (0.3137)		
<i>DISP</i> (+)	-0.0155 (0.0392)	-0.0146 (0.0392)	-0.0169 (0.0394)		-0.0139 (0.0392)	
<i>LEVERAGE</i> (+)	0.0083*** (0.0015)	-0.0024** (0.0010)		0.0082*** (0.0015)	0.0036*** (0.0003)	
<i>MTB</i> (-)	0.2992 (0.1987)		0.2883 (0.1961)	0.3011 (0.1946)	0.0279 (0.1077)	
Firm-Year effects	yes	yes	yes	yes	yes	yes
Sector effects	yes	yes	yes	yes	yes	yes
Nb. obs.	5,552	5,634	5,663	5,835	5,552	6,056
$R^2$ within	0.8745	0.8737	0.8745	0.8708	0.8738	0.8696
Hausman test $\chi^2$	392.11	641.75	1,229.67	636.92	680.38	1,011.88
Prob> $\chi^2$	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001

All estimations are corrected for heteroskedasticity.

\*, \*\* and \*\*\* denote significance at the 10%, 5% and 1% levels, respectively.

Table 6: Statistical summary for regression variables with *MAD* (1999-2011)

<b>PANEL A: Whole period</b>					
% of optimistic forecasts: 47					
Variables	Nb. obs.	Mean	Standard deviation	Min	Max
<i>MAD</i>	7,067	0.65	0.47	0	1

<b>PANEL B: Pre-MAD period</b>					
% of optimistic forecasts: 47					
Variables	Nb. obs.	Mean	Standard deviation	Min	Max
<i>OPTIM</i>	2,404	0.45	2.91	-3.58	10.26
<i>GROWTH</i>	2,404	0.53	0.41	-0.18	1.20
<i>EPSNEGATIVE</i>	2,404	0.08	0.27	0	1
<i>EPSDECLINE</i>	1,943	0.35	0.47	0	1
<i>MONTH</i>	2,404	6.52	3.42	1	12
<i>COVER</i>	2,404	22.88	9.32	1	48
<i>SIZE</i>	2,404	9.01	1.23	5.48	12.12
<i>DISP</i>	2,321	0.65	0.89	0	9.54
<i>LEVERAGE</i>	2,396	374.77	203.21	1	726
<i>MTB</i>	2,367	0.99	1.53	0	17.86

<b>PANEL C: Post-MAD period</b>					
% of optimistic forecasts: 48					
Variables	Nb. obs.	Mean	Standard deviation	Min	Max
<i>OPTIM</i>	4,663	0.72 <sup>+++</sup>	3.20	-3.58	10.26
<i>GROWTH</i>	4,663	0.28 <sup>---</sup>	0.63	-1.61	1.07
<i>EPSNEGATIVE</i>	4,663	0.07	2.63	0	1
<i>EPSDECLINE</i>	4,597	0.33 <sup>-</sup>	0.47	0	1
<i>MONTH</i>	4,663	6.48	3.44	1	12
<i>COVER</i>	4,663	20.85 <sup>---</sup>	8.26	1	47
<i>SIZE</i>	4,663	9.30 <sup>+++</sup>	1.04	5.73	11.92
<i>DISP</i>	4,407	0.70 <sup>-</sup>	1.45	0	22.46
<i>LEVERAGE</i>	4,512	355.37 <sup>---</sup>	211.37	1	738
<i>MTB</i>	4,585	0.75 <sup>---</sup>	0.80	0	6.45

<sup>+++</sup> indicates that the mean in the post-MAD period is significantly higher than in the pre-MAD period at the 1% level.

<sup>---</sup> indicates that the mean in the post-MAD period is significantly weaker than in the pre-MAD period at the 1% level.

<sup>-</sup> indicates that the mean in the post-MAD period is significantly weaker than in the pre-MAD period at the 10% level.

Table 7: Correlation coefficients of *MAD* with other regression variables (1999-2011)

	<i>OPTIM</i>	<i>CSA</i>	<i>GROWTH</i>	<i>EPSNEGATIVE</i>	<i>EPSDECLINE</i>	<i>MONTH</i>	<i>COVER</i>	<i>SIZE</i>	<i>DISP</i>	<i>LEVERAGE</i>	<i>MTB</i>
<i>MAD</i>	0.0410***	0.5286***	-0.2092***	-0.0093	-0.0173	-0.0063	-0.1104***	0.1201***	-0.0188	-0.0442***	-0.1015***

\*\*\* denotes significance at the 1% level.

Table 8: Extension: Results of panel (fixed-effect) regressions with MAD

Variables (expected sign)	[1]	[2]	[3]	[4]	[5]	[6]
<i>CSA</i> (-)	-0.3215** (0.1474)	-0.3203** (0.1453)	-0.3166** (0.1453)	-0.2921** (0.1415)	-0.3429** (0.1494)	-0.2945** (0.1389)
<i>MAD</i> (-)	0.6382 (0.4517)	0.6300 (0.4476)	0.6362 (0.4495)	0.5663 (0.4011)	0.6209 (0.4505)	0.5620 (0.3937)
<i>GROWTH</i> (-)	-0.3102*** (0.0734)	-0.3212*** (0.0729)	-0.3130*** (0.0720)	-0.3066*** (0.0705)	-0.3794*** (0.0772)	-0.3465*** (0.0707)
<i>EPSNEGATIVE</i> (+)	6.8338*** (0.6927)	6.8494*** (0.6967)	6.9038*** (0.6827)	6.6547*** (0.7727)	6.8650*** (0.7126)	6.7876*** (0.7724)
<i>EPSDECLINE</i> (+)	1.9716*** (0.2443)	1.9487*** (0.2422)	1.9521*** (0.2430)	2.0028*** (0.2449)	1.9787*** (0.2467)	1.9524*** (0.2425)
<i>MONTH</i> (-)	-0.0249** (0.0116)	-0.0229** (0.0114)	-0.0254** (0.0114)	-0.0232*** (0.0117)	-0.0261*** (0.0115)	-0.0222** (0.0110)
<i>COVER</i> (-)	0.0336*** (0.0087)	0.0325*** (0.0086)	0.0341*** (0.0087)	0.0335*** (0.0089)	0.0342*** (0.0085)	0.0329** (0.0086)
<i>SIZE</i> (-)	-0.4908* (0.2722)	-0.2723 (0.2060)	-0.4542* (0.2707)	-0.4513* (0.2669)		
<i>DISP</i> (+)	0.00762 (0.0693)	0.0093 (0.0688)	0.0057 (0.0697)		0.0089 (0.0089)	
<i>LEVERAGE</i> (+)	0.0073*** (0.0015)	0.0053*** (0.0006)		0.0074*** (0.0014)	0.0056*** (0.0010)	
<i>MTB</i> (-)	0.2706 (0.1786)		0.2570 (0.1759)	0.2753 (0.1784)	0.0712 (0.1161)	
Firm-Year effects	yes	yes	yes	yes	yes	yes
Sector effects	yes	yes	yes	yes	yes	yes
Nb. obs.	6,005	6,096	6,123	6,301	6,005	6,540
$R^2$ within	0.8339	0.8329	0.8335	0.8242	0.8335	0.8229
Hausman test $\chi^2$	324.05	478.51	594.18	504.61	196.20	684.75
Prob> $\chi^2$	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001

All estimations are corrected for heteroskedasticity.

\*, \*\* and \*\*\* denote significance at the 10%, 5% and 1% levels, respectively.

Table 9: Statistical summary for regression variables with *GS* (1999-2011) **PANEL**

<b>A: Whole period</b>					
% of optimistic forecasts: 47					
Variables	Nb. obs.	Mean	Standard deviation	Min	Max
<i>GS</i>	6,540	0.73	0.44	0	1

<b>PANEL B: Pre-GS period</b>					
% of optimistic forecasts: 46					
Variables	Nb. obs.	Mean	Standard deviation	Min	Max
<i>OPTIM</i>	1,853	0.39	2.86	-3.58	10.26
<i>GROWTH</i>	1,853	0.58	0.41	-0.18	1.20
<i>EPSNEGATIVE</i>	1,853	0.07	0.25	0	1
<i>EPSDECLINE</i>	1,407	0.36	0.48	0	1
<i>MONTH</i>	1,853	6.52	3.42	1	12
<i>COVER</i>	1,853	22.47	8.92	1	48
<i>SIZE</i>	1,853	9.05	1.25	5.48	12.12
<i>DISP</i>	1,795	0.66	0.93	0	9.54
<i>LEVERAGE</i>	1,853	367.41	203.49	1	726
<i>MTB</i>	1,826	1.06	1.65	0	17.86

<b>PANEL C: Post-GS period</b>					
% of optimistic forecasts: 48					
Variables	Nb. obs.	Mean	Standard deviation	Min	Max
<i>OPTIM</i>	5,214	0.71 <sup>+++</sup>	3.18	-3.58	10.26
<i>GROWTH</i>	5,214	0.29 <sup>---</sup>	0.61	-1.61	1.07
<i>EPSNEGATIVE</i>	5,214	0.07	0.27	0	1
<i>EPSDECLINE</i>	5,133	0.33 <sup>---</sup>	0.47	0	1
<i>MONTH</i>	5,214	6.49	3.44	1	12
<i>COVER</i>	5,214	21.21 <sup>---</sup>	8.58	1	47
<i>SIZE</i>	5,214	9.26 <sup>+++</sup>	1.06	5.49	11.92
<i>DISP</i>	4,933	0.69	1.39	0	22.46
<i>LEVERAGE</i>	5,055	360.16	210.65	1	738
<i>MTB</i>	5,126	0.75 <sup>---</sup>	0.82	0	6.45

<sup>+++</sup> indicates that the mean in the post-GS period is significantly higher than in the pre-CSA period at the 1% level.

<sup>---</sup> indicates that the mean in the post-GS period is significantly weaker than in the pre-CSA period at the 1% level.

Table 10: Correlation coefficients of  $GS$  with other regression variables (1999-2011)

	<i>OPTIM</i>	<i>CSA</i>	<i>GROWTH</i>	<i>EPSNEGATIVE</i>	<i>EPSDECLINE</i>	<i>MONTH</i>	<i>COVER</i>	<i>SIZE</i>	<i>DISP</i>	<i>LEVERAGE</i>	<i>MTB</i>
<i>GS</i>	0.0452***	0.4389***	-0.2184***	-0.0150	-0.0292	-0.0046	-0.0634***	0.0809***	-0.0113	-0.0154	-0.1223***

\*\*\* denotes significance at the 1% level.

Table 11: Extension: Results of panel (fixed-effect) regressions with GS

Variables (expected sign)	[1]	[2]	[3]	[4]	[5]	[6]
<i>CSA</i> (-)	-0.3250** (0.1477)	-0.3237** (0.1455)	-0.3200** (0.1456)	-0.2951** (0.1417)	-0.3462** (0.1487)	-0.2973 (0.1391)
<i>GS</i> (-)	-0.3551 (0.2279)	-0.3436 (0.2280)	-0.3491 (0.2284)	-0.2470 (0.2205)	-0.2800 (0.2399)	-0.2024 (0.2237)
<i>GROWTH</i> (-)	-0.3093*** (0.0732)	-0.3203*** (0.0727)	-0.3121*** (0.0718)	-0.3055*** (0.0704)	-0.3787*** (0.0771)	-0.3455 (0.0706)
<i>EPSNEGATIVE</i> (+)	6.8322*** (0.6912)	6.8477*** (0.6952)	6.9021*** (0.6812)	6.6534*** (0.7715)	6.8635*** (0.7112)	6.7861 (0.7713)
<i>EPSDECLINE</i> (+)	1.9702*** (0.2442)	1.9474*** (0.2421)	1.9508*** (0.2429)	2.0018*** (0.2448)	1.9775*** (0.2470)	1.9516 (0.2424)
<i>MONTH</i> (-)	-0.0240* (0.0117)	-0.0220** (0.0115)	-0.0245** (0.0115)	-0.0225** (0.0118)	-0.0253** (0.0116)	-0.0215 (0.0111)
<i>COVER</i> (-)	0.0334*** (0.0087)	0.0323*** (0.0086)	0.0339*** (0.0087)	0.0334*** (0.0089)	0.0340*** (0.0085)	0.0328*** (0.0086)
<i>SIZE</i> (-)	-0.4931* (0.2722)	-0.2740 (0.2060)	-0.4563* (0.2708)	-0.4537* (0.2666)		
<i>DISP</i> (+)	0.0073 (0.0692)	.0091 (0.0687)	0.0055 (0.0696)		0.0087 (0.0690)	
<i>LEVERAGE</i> (+)	0.0087*** (0.0014)	-0.0018* (0.0009)		0.0086*** (0.0013)	0.0069*** (0009)	
<i>MTB</i> (-)	0.2716 (0.1785)		0.1686 (0.3381)	0.2579 (0.1759)	0.2788 (0.1770)	0.0714 (0.1160)
Firm-Year effects	yes	yes	yes	yes	yes	yes
Sector effects	yes	yes	yes	yes	yes	yes
Nb. obs.	6,005	6,096	6,123	6,301	6,005	6,540
$R^2$ within	0.8338	0.8329	0.8334	0.8241	0.8335	0.8228
Hausman test $\chi^2$	482.78	301.39	752.36	521.02	185.29	749.99
Prob> $\chi^2$	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001

All estimations are corrected for heteroskedasticity.

\*, \*\* and \*\*\* denote significance at the 10%, 5% and 1% levels, respectively.