Information Spillovers: The Effect of Analyst Coverage on Returns Co-movement

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Abstract

This paper exploits a mechanism through which sell-side analysts affect correlations across returns on publicly traded stocks. First, I use a set of mergers and acquisitions involving brokerage houses that prompt coverage terminations in a time range spanning from 1984 to 2005. Such events stop coverage but are not informative about fundamental changes to firms' underlying business. Using a differences-in-differences approach, I estimate that returns on affected stocks tend to co-move up to 65% percent more with returns on stocks of industry peers. Second, there is a return premium for stocks covered by fewer analysts even after controlling for betas, size, book-to-market, momentum and liquidity. A trading strategy that buys stocks in the bottom decile of coverage and short-sells those in the top decile yields a statistically significant five-factor alpha of 0.602% per month. Finally, another strategy exploits potential temporary mispricing of the less intensively covered stocks due to excessive co-movement with the intensively covered ones. Strikingly, it yields a statistically significant five-factors alpha of up to 1.246% per month (dependent on specification). Taken together, results suggest that (1) analysts reduce stock returns co-movement by facilitating the incorporation of firm-specific information into prices and (2) investors demand a premium to invest in less intensively covered firms, so that analysts do create value.

Keywords: Information Risk, Co-movement, Analyst Coverage, Information Asymmetry

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1. Introduction

Sell-side analysts act as important intermediaries in financial markets alleviating information asymmetries. Specifically, they offer valuable investment services by aggregating complex information and synthesizing it in a way that is more easily understandable by investors. The empirical literature supports this notion. There is abundant evidence that analysts' recommendations, forecasts and revisions do predict stock price moves and returns[2]. But whereas the direct effect of analyst coverage on prices has been widely studied, its consequences for returns co-movement remain largely unexplored[3]. Accordingly, the main contribution of this paper is to provide enduring evidence of the contribution of analysts to reduce co-movement.

Co-movement across stock returns (as defined by Bekaert, Harvey, and Ng (2005): "excess correlation, that is, correlation over and above what one would expect from economic fundamentals") has been the subject of many studies over the last decade. There is well documented evidence of high levels of correlation and covariance that cannot be fully explained by macroeconomic variables neither by common factors associated with the cross-section of stock returns[4]. The causes of such excessively high levels of correlations remain unclear though. This paper contributes to this debate by shedding light on the role played by analysts in mitigating co-movement.

One possible reason to expect a relationship between analysts' presence and stock return' co-movement relies on the fact that recommendations, forecasts and revisions are targeted at one specific firm. It follows that companies covered by fewer analysts experience a shortage of firm-specific information. In turn, demand for their stocks is more dependent on industry-wide information (which is common for the whole sector). As such commonalities in demand translate into synchronicities in price movement (and therefore in returns), companies followed by fewer analysts will experience higher levels of co-movement with their industry peers. In short, analysts help investors to discriminate among the fundamentals of different companies - and therefore allow prices to incorporate more firm-specific information. *Ceteris paribus*, this mechanism leads to a monotonic negative relationship between the number of analysts covering a firm and the correlation across return on its stock and returns on other firms.

The empirical study of the causal effect that analyst coverage has on co-movement with industry peers poses an empirical challenge though. Analysts might deliberately decide to follow some stocks precisely because their returns are correlated to returns on other stocks into the same industry – saving research time so. Such a possibility raises concerns about reversal causality. In order to avoid this problem, the ideal experiment

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[2] See Givoly and Lakonishok (1979), Lys and Sohn (1990), Francis and Soffer (1997), Womack (1996), Barber, Lehavy, McNichols and Trueman (2001), Barth and Hutton (2000), Jegadeesh and Kim (2004) among others.

[3] To the best of my knowledge, apart from a recent paper by Hameed, Morck, Shen and Yeung (2015), there is no other empirical study of the relationship between analyst coverage and returns co-movement.

[4] See Pindyck and Rotemberg (1993), Vijh (1994) and Barberis, Shleifer, and Wurgler, (2005) for evidence of excessively high levels of correlation across stocks returns – among others. See Anton and Polk (2014) and Greenwood and Thesmar (2011) for evidence of the role played by institutional investors in inducing co-movement.

would be to force analysts to stop doing research on some firms at random and estimate the changes in co-movement that would follow (net of the respective changes experienced by a matched control group). Since this cannot be done, closures and mergers of brokerage houses seem to provide a good setting by creating exogenous shocks to the level of coverage of some companies without major effects to their real operations. The typical situation is that two (or more) analysts from different brokers follow the same company. After a merger or an acquisition takes place they become redundant and one of them is either fired or relocated, leading to a decrease in coverage of the followed company.

In a first set of results, I exploit coverage terminations prompted by 15 mergers involving brokerage houses in a time span ranging from 1984 to 2005. Using such events, I investigate (1) whether there is a premium for stocks covered by fewer analysts and (2) whether stocks followed by fewer analysts display higher levels of co-movement with industry peers. I employ a differences-in-differences estimator (diff-in-diff hereafter) using a time window that spans from four quarters before to four quarters after termination and control for a number of firm-level similarities that could plausibly explain returns and co-movement. Results show (1) a statistically significant increase in average monthly returns[5] and (2) a statistically significant increase in the level of realized intra-quarter correlations across stock returns.

These very events have been used to investigate the effects of coverage on stock liquidity (Kelly and Ljungqvist, 2012), accuracy of earnings forecasts (Hong and Kacperczyk, 2010), firms' investment decisions (Derrien and Kesckés, 2013) and firms' innovative behavior – measured by the number of new patents and the number of forward citations received by such patents (He and Tian, 2013). A crucial matter for the legitimacy of these empirical results is whether these terminations are informative about a firm's fundamentals or not. In case they are, observed shifts in stock returns and correlations might simply be caused by fundamental changes unrelated to the availability of firm-specific information. Results from a diff-in-diff analysis suggest otherwise. I find no statistically significant change in the levels of sales, profitability (measured by ROE), earnings per share, or book-to-market ratio by firms that lose analysts in the events used.

In a second set of results, I use a more extensive sample of US publicly listed firms and a time window that ranges from 1990 to 2010. First, I document a return premium for stocks in the bottom decile of coverage (opaque stocks). A strategy that buys opaque and short sells transparent stocks (those in the top decile of analyst coverage) yields a statistically significant five-factors alpha (using the five-factors model of Pastor and Stambaugh, 2003) of up to 0.602% per month. This result is in line with the notion that investors require a premium to invest in opaque firms, demanding some compensation for the shortage of firm-specific information about these stocks.

Another trading strategy exploits temporary mispricing due to excessive levels of correlation across returns on opaque stocks and their peers. Such a strategy buys shares of companies that seem undervalued by the combination of three factors: low analyst

[5] This increase in stock returns is in line with previous research documented by XXX, who interpret such an increase as investors demanding a premium to invest in a stock about which there is less firm-specific available information. In fact, they argue that less informed investors (such as retail ones) are not willing to trade against better informed ones (such as institutions). I do not dispute this interpretation.

coverage; poor recent stock returns; and belonging to an industry where the non-opaque stocks (expected to be more accurately priced) also had poor returns in the recent months. Analogously, the strategy sells stocks that seem overvalued due to: low analyst coverage; good recent stock return records; and belonging to an industry where the non-opaque stocks also performed well in the recent past. The strategy is intended to exploit return reversals generated by excessive co-movement among stocks due to the shortage of firm-specific information (the very same effect exploited in the events studied). Strikingly, it delivers a positive monthly five-factor alpha with magnitude up to 1.246 % (dependent on the specification). The profitability of such a strategy suggests that opaque stocks might get temporarily under- or overvalued due to excessive co-movement with non-opaque industry peers. A conditions that gets slowly reverted over some months.

A recent paper Hameed, Morck, Shen and Yeung (2015) tangles the connection between analyst coverage and stocks returns co-movement – offering an alternative perspective. Into each sector, they identify companies whose ROA are good predictors of the asset-weighted ROA of their respective industry peers – such firms are then named "bellwether firms". In turn, their findings show that: (1) "bellwether firms" are covered by more analysts; (2) individual analysts' revisions of earnings forecasts of "bellwether firms" provoke price reactions on their industry peers' stocks.

There are at least three important differences between their paper and mine. First, they are primarily concerned with the antecedents of analyst coverage (exploring the effects of coverage as a secondary point), whereas my focus is completely on the consequences of coverage for expected returns and correlations across returns. Second, whereas my proposed mechanism derives an unambiguous prediction regarding the relationship between coverage and co-movement (it predicts that more coverage will always decrease co-movement), their paper suggests ambiguous predictions regarding such a relationship. On one hand, the more analysts a firm has, the more accurate its price will be, and the more frequently its revisions will be used by investors as signals about other firms' earnings – thus increasing co-movement. On the other hand, the fewer analysts a firms has, the more frequently revisions of other firms' earnings (especially the "bellwether firms) will affect its stock price, therefore increasing co-movement as well. It seems to be the case that such a mechanism predicts a U-shaped relationship between coverage and co-movement. Third, as they focus on the unilateral effect of revisions earnings of "bellwether firms" they only look at price reactions to revisions and completely overlook correlations across returns – which is the central analysis made here.

The remaining of this paper is organized as follows. Section 2 describes the data sources and explains the measurement of co-movement. Section 3 describes the empirical strategy used to extract estimations from a natural experiment and presents my main empirical results. Still in this section, I conduct several tests and discuss the validity of the experiment. Section 4 describes a series of trading strategies formulated with the purpose of further quantifying the effect of coverage on co-movement. Section 5 briefly concludes the paper.

2. Data and Measurement

The main sample used in the analysis of the natural experiment is constructed around 15 mergers of brokerage houses. Such events led to coverage terminations for stocks of a large number of public companies as some analysts became redundant in the process and either got fired or were relocated to cover different companies. The mergers took place between 1984 and 2005 and for each event a window that spans from one year before until one year after the event was created (see table 1 for description of the events). For a stock to be included in the sample (either in the treatment or control group), it must belong to an industry (four digits SIC code) where at least one company lost one analyst due to a brokerage merger.

The analysis and measurement of co-movement is done at both the stock and the stock-pair levels of analysis. At the stock level, a firm is included in the treatment group if it effectively lost one analyst due to one of the merger events among brokers. The co-movement is calculated as the correlation across returns on the stocks and returns on an industry index constructed using all the remaining firms in the same industry (4-digits SIC code).

At the stock-pair level, a pair is considered treated if it is formed by one firm that effectively lost one analyst due to a brokerage merge and another stock into the same sector that did not lose any analyst in that process. Control pairs are formed by two stocks that have not been affected by the brokerage merge but that belong to the same industry as a treated pair. At this level of analysis, co-movement is measured as the correlation across returns on each of the shares that form the pair.

In measuring levels of co-movement, I follow Bekaert, Harvey, and Ng (2005) and Anton and Polk (2014) and compute intra-quarter correlations across residuals of an asset pricing model. For each stock-month, I mount a series of daily stock returns and regress it on the realizations of the four factors of Carhart's (1997) model. The residuals of these regressions are (hereafter referred to as 4F residuals) are then used – instead of the raw returns – to compute intra-quarter correlations. This procedure allows me to eliminate part of the correlation across raw returns that is due to exposure to the same underlying risk factors.

As shown in Tables 1 and 2, the sample includes a total number of 1,303 merger-firms, concentrated into 674 merger-industries. With these firms, 804,304 merger-pairs could be formed. The focus on co-movement across returns on stocks of firms operating within the same industry simultaneously rules out the need to otherwise control for industry similarities and concentrates the analysis on pairs of firms with correlated fundamentals - plausibly information about one of them is used by (at least some) investors in order to make inference about the other.

Data on security analysts come from the Institutional Brokers Estimates System (IBES) database. Data on ROE, sales, and book-value come from Compustat. Data on security prices, returns, volumes and fundamentals is gathered from the daily and monthly files from the Center for Research in Security Prices (CRSP). The analysis is restricted to common stocks (share codes 10 and 11) traded at NYSE, AMEX and NASDAQ. I exclude observations with prices below 5 dollars. For the event study my main dependent variable is the within-quarter realized correlation of each stock pair's daily four-factor abnormal returns. Summary statistics are presented in Table 3. *Industry Correlation EW* is the correlation across 4F residuals of stock returns and 4F residuals of returns on an equal-weighted industry index. For the average stock in my sample, there is a 12.5% correlation with the industry index. Average correlation with a value-weighted industry index is 11%. There is positive skewness in the cross section of co-movement with the industry index. This might be due to the presence of the “bellwether firms” documented by Hameed, Morck, Shen and Yeung (2015). The average firm in the sample has a Market Cap equal to 3.6 billion dollars, a book-to-market ratio equal to 0.49, is covered by 4.4 analysts and has a beta equal to 0.79 (computed with the actual S&P 500 series).

For the trading strategies, a more extensive sample is constructed using the intersection between IBES and CRSP's monthly files ranging from 1990Q1 to 2010Q4. In order to be included in the sample, a stock must have been covered by at least one analyst over the whole sample period. Four-factor residuals and alphas are computed using Carhart's model (1997), and five-factor residuals and alphas are computed using the Pástor and Stambaugh's model (2003). Data on (daily and monthly) returns on these factors are collected from the personal websites of Professors Kenneth French and Lubos Pástor.

3. Empirical Results

3.1. Regressions Analysis

I start the analysis of the effect of coverage termination on co-movement at the stock pair-level. I regress the correlation across a stock pair's 4F residuals on a set of variables that includes: one dummy variable set equal to one for treated stock-pairs [6] zero otherwise; one dummy variable set equal to one after the loss of one analysts takes place and zero before; the interaction between these two dummies (the coefficient of this interaction term is indeed the first diff-in-diff estimator); a set of control variables that capture commonalities among the two stocks in the pair terms of size, book-to-market factor, momentum, and ownership. Equation (1) describes the regression.

$$
\begin{aligned}
&corr\left(R_{i,t+1}^{4F}; R_{j,t+1}^{4F}\right) = \\
&\quad = \alpha + \delta_{TREATED*EVENT} * D_{EVENT} * D_{TREATED} + \\
&\quad + \delta_{TREATED} * D_{TREATED} + \delta_{EVENT} * D_{EVENT} + \\
&\quad + \beta_{BIGSIZE} * BIGSIZE_{ij,t} + \beta_{SMALLSIZE} * SMALLSIZE_{ij,t} + \\
&\quad + \beta_{SMALLSIZE*BIGSIZE} * SMALLSIZE_{ij,t} * BIGSIZE_{ij,t} + \\
&\quad + \beta_{SAME\_SIZE} * SAME\_SIZE_{ij,t} + \beta_{SAMEBTM} * SAMEBTM_{ij,t} + \\
&\quad + \beta_{SAMEMOM} * SAMEMOM_{ij,t} + \\
&\quad + \delta_{COMOWNER} * D_{COMOWNER} + \\
&\quad + \beta_{LOGFUNDS} * LOGFUNDS_{ij,t} + \\
&\quad + \beta_{LOGCOVERAGE1} * LOGCOVERAGE1_{ij,t} + \\
&\quad + \beta_{LOGCOVERAGE2} * LOGCOVERAGE2_{ij,t} + \\
&\quad + \beta_{DT*DE*LOGCOV1} * D_{EVENT} * D_{TREATED} * LOGCOVERAGE1_{ij,t} + \\
&\quad + \beta_{DT*DE*LOGCOV2} * D_{EVENT} * D_{TREATED} * LOGCOVERAGE2_{ij,t} + \\
&\quad + \varepsilon_{ij,t} \qquad (1)
\end{aligned}
$$

[6] The level of analysis for these regressions is the stock-pair. For a pair to be included in the treatment sample, (only) one stock must have lost one analyst in a brokerage merger event and the other (unaffected by the event) belongs to the same SIC code. Control pairs are formed using the stocks of two companies that were not affected by the corresponding merger event, but that have the same SIC code as at least one of the affected firms.

In equation (1), D_{EVENT} is a dummy variable set equal to one in the event window – within a one year period after the decrease in analyst coverage – and zero in a window with equal length before the event. $D_{TREATED}$ is set equal to one for treated stock pairs and equal to zero otherwise. $BIGSIZE_{ij,t}$ is the natural logarithm of the market capitalization for the stock of the larger firm in the pair. $SMALLSIZE_{ij,t}$ is the natural logarithm of the market capitalization for the stock of the smaller firm in the pair. $SAMESIZE_{ij,t}$, $SAMEBTM_{ij,t}$ and $SAMEMOM_{ij,t}$ are updated quarterly and computed in a similar manner. Each quarter I calculate every stock's percentile ranking on a particular firm characteristic (market capitalization for $SAMESIZE_{ij,t}$; book-to-market ratio for $SAMEBTM_{ij,t}$; and cumulated return over the last quarter for $SAMEMOM_{ij,t}$). The independent variable introduced to the regression is the negative of the absolute difference in percentile ranking across a pair for a particular characteristic. $D_{COMOWNER}$ is a dummy variable equal to one if there is at least one institution who reports holdings on both stock in the pair at time t. $LOGFUNDS_{ij,t}$ is the log of the number of different institutions who report holdings on both stocks at time at time t. $LOGCOVERAGE1_{ij,t}$ is the natural logarithm of one plus the number of different analysts who cover the stock of the smaller firm in the pair at time t. $LOGCOVERAGE2_{ij,t}$ is the natural logarithm of one plus the number of different analysts who cover the stock of the larger firm in the pair at time t. An analyst is considered to be covering a stock if he or she has issued at least one EPS forecast (the most common forecast found at IBES) over the twelve months period ending at the end of quarter t. Table 4 presents the parameter estimations extracted from these regressions.

$\delta_{TREATED*EVENT}$ is the one parameter in which I am interested the most: it is the coefficient of the interaction of the dummies $D_{TREATED}$ and D_{EVENT}. I reject the null hypothesis that such parameter is equal to zero (with statistical significance at the 1% confidence level for each different specification) and get a positive estimation for it. This first test, therefore, supports the notion that coverage terminations result in an increase in return co-movement across individual stocks into the same industry.

In all regressions whose results are shown in table 4, independent variables are standardized to have zero mean and unit standard deviation (except the dummies and the interaction terms). Thus, the intercept provides a meaningful benchmark against which I can estimate the relative importance of the analyst loss for co-movement. In model (4), for instance, my estimation of $\delta_{TREATED*EVENT}$ corresponds to a 63% of the regression intercept estimation, suggesting an economically significant increase in the level of correlation after the event. Assuming an average net decrease in coverage of one analyst, and since the average stock is covered by 4.4 analysts, such an increase occurs when the number of analysts changes from 4.4 to 3.4.

Interaction terms between the level of coverage for each stock in the pair and the dummies for treatment and post-event period are included in model (5). The increase in correlation is stronger when the smaller company in the pair is followed by fewer analysts (the estimation of $\beta_{DT*DE*LOGCOV1}$ is negative with 1% statistical significant) and when the larger company in the pair is followed by more analysts (the estimation of $\beta_{DT*DE*LOGCOV2}$ is positive with 5% statistical significant). This suggests that the marginal contribution of each analyst to mitigate co-movement is decreasing in the level of coverage (assuming that larger firms tend to be followed by more analysts).

One could argue that the analyst lost in the merger involving brokerage houses is not randomly chosen: likely the worse amongst the two analysts is the one that gets fired or reallocated. Assuming so implies that the estimated change in the level of co-movement are biased downwards (assuming that forecasts and revisions issued by a worse analysts have a weaker impact on stock prices). Therefore, it is very likely that coverage terminations affect levels of co-movement even more than my estimations suggest.

3.2. Control Benchmarks

It is possible that the number of analysts following a given company is somehow associated to the correlation between the stock's own returns and returns on other stocks (raising endogeneity concerns). Analysts might chose to follow a given company precisely because its business is highly correlated to others' and, therefore, in order to save research time. The use of events where coverage is terminated due to brokerage mergers somewhat attenuates the concerns towards the parameters estimated in regressions reported in the previous subsection. A further and stronger test is conducted in the present subsection though. Namely, I use the benchmark-adjusted diff-in-diff (BDID hereafter) estimator used by Hong and Kacperczyk (2010).

Following Hong and Kacperczyk closely in constructing the benchmarks, I first sort stocks into tercile portfolios according to their size (natural logarithm of market capitalization). Next, I sort stocks within each size portfolio according to their book-to-market ratios. This sort results in nine different benchmark portfolios. Further, I sort stocks in each of the nine portfolios into tercile portfolios according to last quarter's cumulative returns, which results in 27 different benchmark portfolios. Finally, I sort stocks in each of the 27 portfolios into tercile portfolios according to their level of analyst coverage. Overall, the benchmark includes 81 different portfolios. Treated stocks are then assigned to their own benchmark portfolios. I require at least three control firms with available data to use a given benchmark. Portfolios’ construction and assignments are updated every quarter.

Thus, for each stock in the treatment sample, the net change in any given characteristic C after the event (the brokerage merger and the resulting analyst loss) is estimated as in equation (2).

$$BDID^{i} = \left(C^{i}_{T,2} - C^{i}_{T,1}\right) - \left(C^{i}_{C,2} - C^{i}_{C,1}\right) \qquad (2)$$

First, an in order to check the validity of my natural experiment, I use this BDID approach to check for differences in analyst coverage, profitability (measured by ROE), EPS, levels of sales. Table 5 presents the results from this analysis. This test is crucial for the validity of the approach. In case there are significant changes in the real operation of firms that lose one analyst, any swings I observe in the covariance matrix of stock returns might be pure consequence of such real changes.

In table 5, only three statistically significant changes can be observed after the merger. First, there is a drop in analyst coverage (measured as the number of different analysts who issued at least one EPS forecast for company i over the period of a quarter). The decrease in analyst coverage is consistent with the identification strategy and, in fact, this is the main effect to which I attribute causation of all others. The fact that on average the decrease in coverage is smaller than one (on average, affected firms are followed by 0.6 fewer analysts) suggests that sometimes both analysts are kept. Presumably, this biases downwards the estimation of the effect of coverage on co-movement. Second, there is an increase in realized monthly stock returns (a statistically significant increase of 0.4% or 0.5% on annualized returns). This is consistent with the notion that investors require a premium to invest in companies covered by fewer analysts. Third, there is a drop in turnover. No statistically significant moves (in either direction) are observed in ROE, EPS, log of sales, size, or book-to-market ratio.

The decrease in liquidity and the increase in realized returns are consistent with previous research documented by Kelly and Ljungqvist (2012). They interpret this decrease in liquidity the result of the refusal of the less informed investors to trade against the better informed ones. Consistently, they interpret the increased average returns as compensation for the liquidity drop. Figure 1, 2 and 3 shows the shifts in levels of analyst coverage, turnover and monthly returns over a time window that spans from one year before until one year after the merger event.

3.3. Correlations

In this subsection, I use the BDID to estimate the net changes in co-movement across returns on stock i (affected by the merger with the loss of one analysts) and returns on an industry index constructed using other stocks within the same four digit SIC code. Again, the comparison against benchmarks constructed using the control sample the matching process should net out the effects of unobserved heterogeneity and work as a better (in comparison to the regressions) estimator for the effect of coverage on co-movement.

The result of such estimation can be seen in table 5. There is a statistically significant increase in correlation across 4F residuals of returns on stock i and its industry’s index (stock i's are not included in the computation of the industry indexes). The magnitude of the increase ranges from 0.9% to 1.6% depending on the weighting scheme adopted to construct the index. The increase in co-movement is stronger when equal weights are used as opposed to a value-weighted index, for instance. This suggests that bigger firms are not necessarily the ones used as alternative source of information by investors when coverage is absent. The same can be said about firms with high levels of volume or coverage (which one could think of as more visible firms). Figure 4 shows the shifts in within-quarter correlations between returns on stock i and the equal-weight industry index over a time window that spans from one year before until one year after the merger event.

Finally, I use the BDID at the stock-pair level in order to estimate changes in the correlation across returns on two individual stocks. Using the same portfolios assignment (matched in terms of size, book-to-market ratio, momentum and coverage), I compare treated stock pairs (pairs in which one stock has lost an analyst due to the brokerage merger and the other one belongs to the same industry but has not been affected by the merger) against control pairs (in which neither stock experienced coverage reduction because of the brokerage merger, but formed by two stocks that belong to an industry where at least one other firm was affected). Again, I demand at least three other stock-pairs with available data in order to use a given benchmark. Also, for each treated pair, I require that the non-affected stock be different from each of the two stocks used to form each of the control-pairs. Table 7 presents results for these estimations.

As table 7 shows, there is a statistically significant increase in the correlation across 4F residuals of returns on individual stocks. The magnitude of the increase is equal to 0.3% – substantially smaller in magnitude than the increase in co-movement across returns on the individual stocks affected with the loss of an analyst and returns on an industry index. Figure 5 shows the shifts in within-quarter correlations for treated stocks (net of the correlation for the benchmark control pairs).

4. Discussion

There are at least four other papers that use identification strategies similar to mine. First, Kelly and Ljungqvist (2012) use a set of 43 brokerage closures and mergers that resulted in analyst coverage terminations in order to study theoretical predictions of information asymmetry models. They interpret such terminations as events that exacerbate the information asymmetry between institutions and retail investors by removing one public signal. Since individuals are more likely to rely on the reports produced by analysts for buying/selling decisions, the information gap between those two groups is more salient after coverage is reduced. The authors show that institutional ownership increases, liquidity decreases and expected returns increase after coverage is reduced (in my sample I am able to replicate two of these three results, but I do not observe statistically significant increase i institutional ownership). They interpret the increase in expected return as compensation investors require after liquidity dries up.

Second, Derrien and Kesckés (2013) use a sample of 53 brokerage closures and mergers to evaluate the real effects of analyst coverage on corporate investment and financing policies. The find support for the hypothesis that reductions in analyst coverage increase the cost of capital and, consequently, decrease the profitability of projects and the optimal amount of investment. Likewise, since the cost of external financing increases both in absolute terms and relative to the cost of internal financing, they find that the optimal amount of external financing decreases as well. In sum, they show that coverage terminations cause a decrease in investment and financing.

Third, Hong and Kacperczyk (2010) use the very same events that are used here to identify decrease in analyst coverage and show that as competition among analysts decreases, bias in earnings forecasts (measured by the difference between realized actual earnings and forecasted earnings by analysts) increases. Their interpretation is that coverage terminations relieve the competition among the remaining analysts and, in turn, the quality of their research (measured by the bias of reports produced).

Fourth, He and Tian (2013) use a sample of coverage terminations prompted by 23 mergers and 15 independent closures involving brokerage houses. They study the effect of coverage on firm's innovate behavior. Their main hypothesis is that analysts exert too much pressure on managers to meet short-term goals and keep firms from making long-term investments in innovative projects. Accordingly, they find that after coverage terminations, firms generate more patents and patents with higher impact.

Except by Kelly and Ljungqvist (2012), none of the above mentioned studies presents any hint on the cross-sections implications of analyst coverage for co-movement. Kelly and Ljungqvist, though, touch it as a side point. Liquidity plays a central role in their theory. When one public signal about the future prospects of a stock is missed, individual investors hesitate to trade against better informed institutional investors. In turn, liquidity decreases and, as it gets incorporated to prices, expected returns increase and prices fall in the announcement dates of the coverage decrease. They analyse the abnormal returns of portfolios composed by stocks in the same industry as the stock that loses one analyst - excluding the single stock that happens to have a coverage decrease. They find that such portfolios also have negative abnormal returns in the announcement dates (but weaker in magnitude in comparison to the stocks that lost an analyst). They do not evaluate, however, shifts in correlations and swings in co-movement due to coverage decreases, which is the main goal of this paper.

Also, the liquidity decreasing mechanisms explained by Kelly and Ljungqvist may be initially seen as a concern for my empirical analysis. One could think that my results are totally or partially driven by the same mechanism. But we shall keep in mind that my focus is on stock pairs where only one of the stocks loses one analyst - so that one of the stocks in the pair experiences a decrease in liquidity and the other does not. The liquidity-driven mechanism provides no unequivocal prediction for the change in co-movement in this setting. It is not clear if co-movement should decrease or increase - in fact, it depends on whether the other stock in the pair is more or less liquid than the one stock that lost and analyst. On the other hand, the theory presented here predicts that, after the loss of one public signal, investors will make more inference from prices of other stocks in the same industry to evaluate firms. Accordingly, I predict an increase in co-movement after one analyst is released or relocated while the liquidity mechanism is silent with respect to co-movement. Anyway, the trading strategy developed in next section do take into account the effect of liquidity. Since they are still profitable strategies, it seems that the liquidity does not tell the full history.

5. Trading Strategies

In order to further asses the asset pricing consequences of analyst coverage, this section studies stock return patterns somehow associated to the number of analysts following a given firm.

5.1. Opaque vs Transparent Stocks

I first focus on the estimation of a possible premium for opaque stocks. Previous research has shown (Kelly and Ljungqvist, 2012) that investors demand a premium to hold stocks of companies followed by fewer analysts, a theoretical prediction of Easley and O'Hara (2004).

Using data from CRSP monthly files and IBES I sort stocks according to the number of analysts who issued at least one EPS forecast over the last twelve months. Stocks in the top decile (followed by the largest number of analysts) are referred to as transparent stocks. Stocks in the bottom decile (followed by the lowest greater-than-zero number of analysts) are referred to as opaque stocks. Using Pastor and Stambaugh's (2003) five-factor model, I estimate alphas for the portfolio formed by opaque stocks, for the portfolio formed by transparent stocks, and for the long-short portfolio that goes long on the former and short on the latter group. I vary the holding period from 3 up to 36 months. Table 8 presents alpha estimations for the profitability of these strategies.

There is a premium for both opaque and transparent stocks. But the premium for the opaque seems to be significantly greater in magnitude. Breaking down the analysis in two distinct ten-years periods shows that the premium for opaque stocks is more concentrated in the latter ten years period ranging from 2000 to 2010[7]. It ranges from 0.84% to 0.90% in such period, as opposed to a range between 0.63% and 0.87% in the earlier ten years period from 1990 to 2000. The premium for transparent stocks, on the contrary, is more concentrated on the first half of the sample. Between 1990 and 2000 such premium ranges from 0.37% to 0.44%, whereas in the latter tan years period between 2000 and 2010 the range is in between 0.25% and 0.37%.

Alphas for the long-short portfolios add up to 0.898 % per month with a holding period equal to 36 months in the second half of the time period. The statistically significant difference in alphas suggests that the premium for opaque stocks cannot be completely explained away by their lower levels of liquidity (since one of the five factors in the PS, 2003, model is attributed the premium for less liquid securities).

[7] This is surprising given that the Regulation Fair Disclosure (Reg FD) was promulgated in 2000. One could expect that the value added by analysts would be attenuated with less selective disclosure, but that is exactly the opposite of what is observed.

5.2. Co-movement of Opaque Stocks

To provide another measure of how strong is the effect of coverage on co-movement, I develop a set of trading strategies that exploit predictable return patterns generated by such effect. In order to implement the strategies, every month I sort stocks per industry according to the number of analysts who issued at least one EPS forecast over the last twelve months period. Only the stocks in the bottom quintile (followed by fewer analysts, and therefore opaque) are used to construct the portfolios used here. The opaque stocks, into each industry, are further sorted according to cumulated stock return over the last 3/12/24/36 months. Stocks into the top quintile are the opaque-winners, while the ones in the bottom quintile are the opaque-losers. In parallel, I sort industries according to the average cumulated return of the non-opaque stocks over the last 3/12/24/36 months. Industries in the top quintile are the winner-industries, while industries in the bottom quintile are the loser-industries. According to the theoretical mechanism I investigate, I expect the opaque-loser stocks from loser-industries to be temporarily undervalued. These firms might be suffering the consequences of an excessive co-movement with peers that show a poor recent performance record. I, therefore, expect that these stocks will experience positive abnormal returns in the upcoming months. Therefore, the long portfolio is built with these stocks (using equal weights). A similar reasoning suggests that stocks that are opaque-winners into a winner-industry might be overvalued (because of excessive co-movement with industry peers that have performed very well in the recent past). Accordingly, these are the stocks that form the short portfolio for this second set of trading strategies.

In sum, the trading strategy studied in this section consists on buying stocks that seem to be undervalued due to the combination of three factors: low analyst coverage; poor recent stock returns; and belonging to an industry where the non-opaque stocks (expected to be more accurately priced) also had poor returns in the recent months. If the mechanism I identify holds for a larger sample of securities than the one used for the event studies analysis, these stocks should be systematically undervalued, suffering the temporary effects of excessive co-movement with other stocks that presented poor performance in the recent past. Simultaneously, the strategy short sells likely overvalued stocks - those with low levels of coverage, good recent stock return records and whose non-opaque industry peers also performed well in the recent past. Table 9 presents alpha estimations for the profitability of these strategies when I vary the holding period from 3 to 36 months.

The analysis of the resulting alphas of this trading strategy is very rich. When using the cumulated returns for opaque and non-opaque stocks over shorter periods of time (of 3 and 12 months) to form the long and short portfolios, both of them yield positive and statistically significant alphas. As the formation period is enlarged (to 24 or 36 months), the alphas for the short portfolios lose statistical significance. However, the magnitude of alphas for the long portfolios increases. For long holding periods (of 12 or more months), the difference becomes statistically significant as well (no matter which formation period is used), suggesting a slow moving price correction. The observed alphas for the short portfolios can be understood as the net result of two competing effects: the premium for opaque stocks (recall that opaque stocks are used to form both short and long portfolios in this trading strategy); and the price correction suffered by a temporarily overpriced stock (due to excessive co-movement with industry-peers that display good performance records in the recent past). For instance, when both formation and holding periods are set equal to 24 months, the long portfolio (formed by stocks that are opaque, with poor recent cumulated returns and whose industry peers also show a poor recent cumulated return) yields a positive and statistically significant alpha equal to 1.197% per month (15.348% per year), whereas the short portfolio (formed by stocks that are opaque, with good recent cumulated stocks returns and whose industry peers also show good recent cumulated returns) has a positive alpha equal to 0.030% per month (0.361% per year) which is not statistically distinct from zero.

One possible interpretation is that, over this 24 months window, the stocks in the long portfolio display positive alphas resulting from the combination of the two factors: being an opaque stock; and a price adjustment for an initially undervalued stock because of excessive co-movement with poorly-performing industry peers. At the same time, stocks in the short portfolio could be experiencing two effects that offset each other (so that the observed net alpha is not statistically different from zero). First, there is a return premium for opaque stocks. Second, there is a low frequency price adjustment experienced by an initially overpriced stock. This interpretation is consistent with my estimation of the premium for opaque stocks (in my first trading strategy), which is equal to 0.87% per month using a holding period of 24 months. It is in between the magnitudes of the alphas for the long and the short portfolios in the second trading strategy. Figure 6 shows the profitability of the trading strategies.

6. Conclusion

This paper measures the effect of the supply of firm-specific information (measured by the number of sell-side analysts who follow a specific firm) on stock returns co-movement. As the number of analysts following a firm is very likely to be endogenous to many characteristics of the firm, I use a natural experiment - namely, mergers of brokerage houses, which result in the firing of analysts as some become redundant. I use these terminations to quantify the causal effect of analyst coverage on returns co-movement. I find that these exogenous reductions in the number of analysts covering a company lead the stock of such company to co-move more with stocks of other firms operating within the same industry.

The economic reasoning is that investors face a shortage of firm-specific information and use available information about other firms operating into the same sector to form inferences about fundamentals. Exploiting the same mechanisms, I develop two trading strategies and show that (1) investors require a premium for holding opaque stocks (followed by fewer analysts) and (2) a shortage of coverage (and therefore of firm-specific information supply) leads opaque companies to get temporarily under- or overvalued due to excessive co-movement with stocks of competitors.

These findings have important implications for market efficiency - highlighting the role analysts play in the incorporation of information to prices - and for portfolio selection - as analyst are found to affect levels of correlations across stock returns. Also, the evidence presented here contributes to the debate on the reasons for excessive co-movement (levels of correlation that go above and beyond expected, given economic fundamentals) by quantifying the effect of information supply on it.

Table 1

This table shows the events used for the event studies. It includes the names of brokerage houses involved in the mergers, the date of the merger, and the number of stocks covered by either brokerage house or by both of them prior to the merger. The treatment sample is constructed using pairs of stocks in which one stock was affected by one of the mergers and the other one was not. The control sample includes pairs of stocks where neither firm was affected by the merger events but another firm within the same industry was.

Bider	Target	Merger Date	Stocks Covered by the Bidder	Stocks Covered by the Target	Stocks Covered by both
Merrill Lynch	Becker Paribas	10-Sep-84	762	288	168
Wheat First Securities	Butcher & Co., Inc.	31-Oct-88	178	66	3
Paine Webber	Kidder Peabody	31-Dec-94	659	545	176
Morgan Stanley	Dean Witter Reynolds	31-May-97	739	470	210
Smith Barney (Travelers)	Salomon Brothers	28-Nov-97	914	721	242
EVEREN Capital	Principal Financial Securities	9-Jan-98	178	142	8
DA Davidson & Co.	Jensen Securities	17-Feb-98	76	53	8
Dain Rauscher	Wessels Arnold & Henderson	6-Apr-98	360	135	6
First Union	EVEREN Capital	1-Oct-99	274	204	20
Paine Webber	JC Bradford	12-Jun-00	516	182	23
Credit Suisse First Boston	Donaldson Lufkin and Jenrette	15-Oct-00	856	595	247
UBS Warburg Dillon Read	Paine Webber	10-Dec-00	596	487	137
Chase Manhattan	JP Morgan	31-Dec-00	487	415	44
Fahnestock	Josephthal Lyon & Ross	18-Sep-01	117	91	5
Janney Montgomery Scott	Parker/Hunter	22-Mar-05	116	54	6

Table 2 – Mergers of Brokerage Houses

This table shows the number of firms and industries affected by the merger events. In total there are 674 merger-industry groups, 12,984 merger-firms (1,303 affected firms and 11,681 used for control), and 805,304 merger-pairs (32,038 treated pairs and 772,266 pairs used for control). It also displays the percentage of affected firms and treated pairs in the sample.

Merger Data	Affected Firms	Affected Industries	Control Firms	Affected Firms (%)	Treatment Pairs	Control Pairs	Treatment Pairs (%)
10-Sep-84	168	101	1,222	13.75%	2,959	67,038	4.41%
31-Oct-88	3	3	90	3.33%	90	4,668	1.93%
31-Dec-94	176	79	1,145	15.37%	4,052	48,220	8.40%
31-May-97	210	101	1,513	13.88%	5,271	83,890	6.28%
28-Nov-97	242	107	1,673	14.47%	5,540	93,540	5.92%
9-Jan-98	8	7	349	2.29%	407	27,898	1.46%
17-Feb-98	8	8	163	4.91%	163	5,844	2.79%
6-Apr-98	6	5	102	5.88%	112	2,816	3.98%
1-Oct-99	20	15	673	2.97%	1,248	78,982	1.58%
12-Jun-00	23	15	532	4.32%	743	65,928	1.13%
15-Oct-00	247	137	2,080	11.88%	5,541	160,486	3.45%
10-Dec-00	137	64	1,210	11.32%	3,459	71,600	4.83%
31-Dec-00	44	23	748	5.88%	2,142	53,768	3.98%
18-Sep-01	5	3	90	5.56%	220	4,628	4.75%
22-Mar-05	6	6	91	6.59%	91	2,960	3.07%
TOTAL	1,303	674	11,681	5.46%	32,038	772,266	3.98%

Table 3 – Descriptive Statistics

This table shows the summary statistics for the distributions of the main variables used in the empirical analysis. 'Industry Correlation EW' is the intra-quarter correlation between returns on a given stock and an equally-weighted industry index constructed using all the other firms within the same industry with available data at the CRSP's daily data file (stock-quarters in which less than 5 other firms are available to construct the industry index are discarded). Instead of the raw returns, residuals of regressions using Carhart's (1997) 4-factors model are used to compute such correlations (for both single stocks and industry-index returns). 'Industry Correlation VW' are constructed in a similar manner but using a value-weighted industry index. 'Market Cap' is computed as the product between share price and the number of shares outstanding. 'Book-To-Market Ratio' is the ratio between the book value and 'Market Cap' . 'Coverage' is the number of sell-side analysts following a given stock at a given point in time. An analysts is considered to be covering a stock if he has issued at least one forecast of earnings per share (EPS) in the last twelve months. 'Volatility' is computed per month using daily data from CRSP. 'Turnover' is computed as the ratio between volume of transactions and the number of shares outstanding from CRSP's monthly files. 'Beta SP 500' is estimated from intra-quarter regressions using daily data for returns on the S&P 500 index. 'Institutional Ownership' is computed as the percentage of shares outstanding held by institutional investors with $100 million or more in assets under management (who are required to file quarterly 13f reports).

Variable	Obs	Mean	Stardard-Deviation	Pctl 5	Pctl 25	Pctl 50	Pctl 75	Pctl 95
Industry Correlation EW	12,746	0.125	0.150	-0.038	0.026	0.082	0.182	0.450
Industry Correlation VW	12,746	0.110	0.164	-0.057	0.004	0.056	0.161	0.478
Market Cap (Millions)	12,984	$3,779.45	$17,155.01	$28.17	$123.07	$426.84	$1,663.98	$13,379.86
Book-To-Market Ratio	11,550	0.489	0.498	0.074	0.226	0.399	0.640	1.138
Coverage	11,172	4.395	3.720	1.000	1.750	3.083	5.833	12.091
Volatility	12,982	3.594%	2.053%	1.227%	2.016%	3.046%	4.722%	7.700%
Turnover	12,982	7.416	8.558	0.651	2.162	4.370	9.669	23.783
Beta SP 500	12,981	0.787	0.635	0.054	0.341	0.643	1.069	2.093
Institutional Ownership	12,640	13.602%	10.906%	0.618%	4.533%	11.217%	20.568%	34.411%

Table 4 – Regressions Analysis

This table presents results from the regressions analysis conducted using a time-window that spans from 4 quarters before to 4 quarters after the brokerage merger. The dependent variable is the realized intra-quarter correlation across residuals of regressions of daily returns for each stock in the pair on Carhart's (1997) 4-factors model. 'DEvent' is a dummy variable set equal to one after the merger and to zero before. 'DTreatment' is a dummy for treated stock-pairs. 'SimBTM', 'SimMom3m' and 'SimSize' are computed in a similar manner. Every quarter, stocks are sorted according to their book-to-market ratio, cumulated return over the last three months, and market capitalization, respectively. The negative of the absolute value of the difference between the percentiles ranking of each stock in the pair form the respective independent variable. 'SmallSize' is the natural logarithms of the market capitalization for the stock with smaller market value in the pair. 'BigSize' is the natural logarithms of the market capitalization for the stock with larger market value in the pair. 'DComOwner' is a dummy variable set equal to one there is at least one institutional investors that holds both stocks in the pairs at time t. 'logNumberOfFunds' is the natural logarithm of the number of institutional investors that hold both stocks at time t. 'LogCov1' is the natural logarithm of one plus the number of different analysts who issued at least one earnings per share forecast for the larger firm in the pair over the three months preceding t. 'LogCov2' is the natural logarithm of one plus the number of different analysts who issued at least one earnings per share forecast for the smaller firm in the pair over the three months preceding t.

Variable	Model1	Model2	Model3	Model4	Model5
Intercept	0.024	0.112	0.192***	0.137***	0.202***
	(-1.01)	(1.613)	(3.475)	(2.833)	(2.785)
DEvent	0.038***	0.038**	0.036*	0.008	0.036
	(2.830)	(2.089)	(1.950)	(0.498)	(1.250)
DTreated	0.268***	0.108***	0.073*	0.091***	0.124***
	(8.044)	(3.038)	(1.959)	(2.632)	(2.808)
DTreated*DEvent	0.079***	0.069***	0.071***	0.087***	0.253***
	(4.125)	(3.102)	(3.144)	(3.653)	(5.357)
SimBTM		0.033***	0.032***	0.032***	0.044***
		(4.817)	(4.766)	(4.678)	(4.206)
SimMom3m		0.054***	0.052***	0.050***	0.070***
		(7.484)	(7.011)	(6.992)	(6.813)
SimSize		0.028	-0.123***	-0.111***	-0.185***
		(0.664)	(-3.83)	(-3.77)	(-3.81)
SmallSize		0.301***	0.373***	0.226***	0.331***
		(4.404)	(6.827)	(5.588)	(4.286)
BigSize		0.006	-0.104**	-0.103***	-0.203***
		(0.114)	(-2.50)	(-2.61)	(-3.52)
SmallSize*BigSize			0.106***	0.094***	0.096***
			(6.411)	(6.053)	(3.688)
DComOwner			0.009		
			(0.596)		
logNumberOfFunds				0.153***	0.181***
				(5.506)	(5.191)
DT*DE*logCov1					-0.158***
					(-6.26)
DT*DE*logCov2					0.048**
					(2.125)
R-square	1.40%	8.50%	9.10%	10.00%	12.50%
Denominator DF	608	594	594	594	577
Number of Obs	1,235,350	1,004,320	1,004,320	1,004,141	543,122

Table 5 – BDID of Individual Firms Characteristics

This table shows the Diff-in-Diff estimations of changes in firm characteristics for stocks that lost one analyst due to the mergers involving brokerage houses. Each quarter, benchmark portfolios are formed using stocks in the control sample based on stocks' size (SIZE), book-to-market ratio (BTM), cumulated past quarter's return (MOM) and the number of analysts who issued at least one EPS forecast for the firm over the last twelve months (COVERAGE). The benchmark assignment involves three portfolios in each category. Each stock in the treatment sample is assigned to its own benchmark SIZE/BTM/MOM/COVERAGE-matched. I then compute the difference in the level of each characteristic and the average of its corresponding benchmark. Finally, I regress these differences on a dummy variable set equal to one for the post-event period and zero for the pre-event period (BDID estimator). Following Bertrand, Duflo and Mullainathan (2004), either standard-errors are clustered or observations are collapsed so that I have only one observation for each period (pre- or post-event) per stock. Observations with stock prices lower than $5 are excluded, as well as EPS forecasts for which the absolute difference between forecast value and the true earnings exceeds $10. (***), (**), and (*) represent 1%, 5%, and 10% statistical significance respectively.

Variable	Parameter	Clustering Standard Errors	Collapsing Observations per Period
Coverage	Coefficient	-0.632***	-0.602***
	Observations	9482	2467
	PValue	0	0
	TStat	(-6.56)	(-3.65)
Size	Coefficient	0.027	0.066
	Observations	33282	2464
	PValue	0.104	0.117
	TStat	(1.625)	(1.567)
BTM	Coefficient	0.018	0.02
	Observations	8928	2322
	PValue	0.121	0.23
	TStat	(1.552)	(1.200)
Return	Coefficient	0.421***	0.479***
	Observations	33282	2464
	PValue	0.003	0
	TStat	(3.006)	(3.529)
Turnover	Coefficient	-0.141***	-0.126**
	Observations	33282	2464
	PValue	0	0.013
	TStat	(-3.63)	(-2.48)

Table 5 – BDID of Individual Firms Characteristics (continued)

This table shows the Diff-in-Diff estimations of changes in firm characteristics for stocks that lost one analyst due to the mergers involving brokerage houses. Each quarter, benchmark portfolios are formed using stocks in the control sample based on stocks' size (SIZE), book-to-market ratio (BTM), cumulated past quarter's return (MOM) and the number of analysts who issued at least one EPS forecast for the firm over the last twelve months (COVERAGE). The benchmark assignment involves three portfolios in each category. Each stock in the treatment sample is assigned to its own benchmark SIZE/BTM/MOM/COVERAGE-matched. I then compute the difference in the level of each characteristic and the average of its corresponding benchmark. Finally, I regress these differences on a dummy variable set equal to one for the post-event period and zero for the pre-event period (BDID estimator). Following Bertrand, Duflo and Mullainathan (2004), either standard-errors are clustered or observations are collapsed so that I have only one observation for each period (pre- or post-event) per stock. Observations with stock prices lower than $5 are excluded, as well as EPS forecasts for which the absolute difference between forecast value and the true earnings exceeds $10. (***), (**), and (*) represent 1%, 5%, and 10% statistical significance respectively.

Variable	Parameter	Clustering Standard Errors	Collapsing Observations per Period
Beta SP 500	Coefficient	-0.022	-0.026
	Observations	33282	2464
	PValue	0.318	0.272
	TStat	(-1.00)	(-1.10)
Institutional Ownership	Coefficient	-0.327	-0.299
	Observations	9442	2463
	PValue	0.112	0.426
	TStat	(-1.59)	(-.796)
ROE	Coefficient	1.93	3.7
	Observations	792	611
	PValue	0.387	0.136
	TStat	(0.866)	(1.492)
Log of Sales	Coefficient	-0.056	-0.023
	Observations	3110	775
	PValue	0.114	0.786
	TStat	(-1.58)	(-.272)
Earnings per Share	Coefficient	0.064	0.015
	Observations	3114	776
	PValue	0.169	0.785
	TStat	(1.379)	(0.273)

Table 6 – BDID of Co-movement with Industry Index

This table shows the Diff-in-Diff estimations of changes in correlations across individual stock and industry index returns. Each quarter, benchmark portfolios are formed using stocks in the control sample based on stocks' size (SIZE), book-to-market ratio (BTM), cumulated past quarter's return (MOM) and the number of analysts who issued at least one EPS forecast for the firm over the last twelve months (COVERAGE). The benchmark assignment involves three portfolios in each category. Each stock in the treatment sample is assigned to its own benchmark SIZE/BTM/MOM/COVERAGE-matched. I compute the intra-quarter correlation across daily stock returns on a given stock and an index formed by the other stocks belonging to the same industry. Instead of raw returns, I use residuals of the four-factor Carhart model (1997). I calculate the difference in the levels of correlation with the industry index between each treated stock and the average of its corresponding benchmark. Finally, I regress these differences on a dummy variable set equal to one for the post-event period and zero for the pre-event period (BDID estimator). Following Bertrand, Duflo and Mullainathan (2004), either standard-errors are clustered or observations are collapsed so that I have only one observation for each period (pre- or post-event) per stock. Observations with stock prices lower than $5 are excluded, as well as EPS forecasts for which the absolute difference between forecast value and the true earnings exceeds $10. (***), (**), and (*) represent 1%, 5%, and 10% statistical significance respectively.

Variable	Parameter	Clustering Standard Errors	Collapsing Observations per Period
Correlation with Industry Equal-Weighted Index (%)	Coefficient	1.625***	1.684**
	Observations	8162	2207
	PValue	0	0.027
	TStat	(3.913)	(2.212)
Correlation with Industry Value-Weighted Index (%)	Coefficient	1.211***	1.275
	Observations	8162	2207
	PValue	0.007	0.126
	TStat	(2.694)	(1.529)
Correlation with Industry Volume-Weighted Index (%)	Coefficient	1.079**	1.127
	Observations	8162	2207
	PValue	0.013	0.128
	TStat	(2.493)	(1.524)
Correlation with Industry Coverage-Weighted Index (%)	Coefficient	0.989**	1.116
	Observations	8082	2175
	PValue	0.023	0.174
	TStat	(2.273)	(1.361)
Correlation with Industry log-Coverage-Weighted Index (%)	Coefficient	0.989**	1.116
	Observations	8082	2175
	PValue	0.023	0.174
	TStat	(2.273)	(1.361)

Table 7 – BDID of Co-movement across Individual Stocks

This table shows the Diff-in-Diff estimations of changes in correlations across returns on individual stock. Each quarter, benchmark portfolios are formed using stocks in the control sample based on stocks' size (SIZE), book-to-market ratio (BTM), cumulated past quarter's return (MOM) and the number of analysts who issued at least one EPS forecast for the firm over the last twelve months (COVERAGE). The benchmark assignment involves three portfolios in each category. Each stock in the treatment sample is assigned to its own benchmark SIZE/BTM/MOM/COVERAGE-matched. I compute the intra-quarter correlation across daily stock returns on two stocks in a pair. Treated pairs are composed by one stock that lost an analyst and another one belonging to the same industry but was not affected by the merger. Control pairs are formed using two stocks that did not lose and analysts but that belong to the same industry as stocks in one treated pair. Instead of raw returns, I use residuals of the four-factor Carhart model (1997). I calculate the difference in the levels of correlation for each treated pair and the average correlation for matched control pairs (where each stock belongs to the same benchmark portfolio as one stock in the treated pair). Finally, I regress these differences on a dummy variable set equal to one for the post-event period and zero for the pre-event period (BDID estimator). Following Bertrand, Duflo and Mullainathan (2004), either standard-errors are clustered or observations are collapsed so that I have only one observation for each period (pre- or post-event) per stock-pair. Observations with stock prices lower than $5 are excluded, as well as EPS forecasts for which the absolute difference between forecast value and the true earnings exceeds $10. (***), (**), and (*) represent 1%, 5%, and 10% statistical significance respectively.

Variable	Parameter	Clustering Standard Errors	Collapsing Observations per Period
Correlation (%)	Coefficient	0.290***	0.359***
	Observations	143927	40024
	PValue	0.001	0.001
	TStat	(3.466)	(3.283)

Table 8 – Premium for Opaque Stocks

This table presents the performance of a trading strategy that uses opaque and transparent stocks. Stocks are sorted according to the number of analysts who issued at least one EPS forecast over the last twelve months. Stocks into the top decile (followed by more analysts) form the Transparent Portfolios (using equal weights). Stocks in the bottom decile (followed by fewer analysts) form the Opaque Portfolios (using equal weights). Using Pastor and Stambaugh's (PS, 2003) five-factor model, alphas are estimated for each portfolio and for the portfolios that goes long on the opaque and short on the transparent stocks. Monthly alphas are shown in percentages. Observations with stock prices lower than $5 and those for which the absolute difference between forecast value and the true earnings exceeds $10 are excluded. (***), (**), and (*) represent 1%, 5%, and 10% statistical significance respectively.

Panel A - 1990-2010							
Holding Period	3 Months	6 Months	9 Months	12 Months	18 Months	24 Months	36 Months
Opaque	0.719***	0.759***	0.781***	0.783***	0.811***	0.834***	0.873***
	(7.547)	(7.693)	(7.848)	(7.908)	(8.210)	(8.516)	(9.310)
Transparent	0.361***	0.365***	0.376***	0.393***	0.425***	0.442***	0.440***
	(3.855)	(3.871)	(4.027)	(4.221)	(4.602)	(4.810)	(4.875)
Opaque-Transparent	0.358**	0.394***	0.405***	0.389***	0.386***	0.392***	0.434***
	(2.539)	(2.759)	(2.874)	(2.802)	(2.799)	(2.878)	(3.353)

Panel B - 1990-2000							
Holding Period	3 Months	6 Months	9 Months	12 Months	18 Months	24 Months	36 Months
Opaque	0.626***	0.667***	0.720***	0.733***	0.779***	0.815***	0.864***
	(5.224)	(5.696)	(5.978)	(6.041)	(6.521)	(6.980)	(7.810)
Transparent	0.372***	0.377***	0.398***	0.413***	0.446***	0.453***	0.436***
	(3.651)	(3.706)	(3.844)	(3.918)	(4.113)	(4.159)	(4.116)
Opaque-Transparent	0.255	0.290*	0.322*	0.320*	0.333*	0.362**	0.429***
	(1.633)	(1.806)	(1.932)	(1.882)	(1.954)	(2.191)	(2.827)

Panel C - 2000-2010							
Holding Period	3 Months	6 Months	9 Months	12 Months	18 Months	24 Months	36 Months
Opaque	0.835***	0.858***	0.848***	0.839***	0.855***	0.871***	0.898***
	(6.131)	(6.139)	(6.154)	(6.192)	(6.142)	(6.237)	(6.509)
Transparent	0.253**	0.256**	0.264**	0.285***	0.320***	0.352***	0.372***
	(2.277)	(2.285)	(2.416)	(2.654)	(3.074)	(3.440)	(3.758)
Opaque-Transparent	0.582***	0.602***	0.584***	0.554***	0.535***	0.519***	0.525***
	(3.079)	(3.187)	(3.207)	(3.155)	(3.068)	(3.003)	(3.130)

Table 9 – Return Premium due to Excessive Co-movement

This table presents the performance of trading strategies that exploit temporary mispricing of opaque stocks due to excessive co-movement with non-opaque ones. Within each industry (four-digit SIC code), stocks are sorted monthly according to the number of analysts who issued at least one EPS forecast over the last twelve months. Only stocks followed by at least one analyst are included. Stocks into the bottom quintile (considered opaque) are used to form the Long and Short Portfolios (using equal weights). Within each industry, opaque stocks are further sorted and assigned to quintiles according to the cumulated return over the last 3/12/24/36 months (different formation periods are used). Opaque stocks in the top quintile are the opaque-winners, whereas those in the bottom quintile are the opaque-losers. In parallel, industries are sorted monthly according to the cumulated average return of the non-opaque stocks over the last 3/12/24/36 months. Industries in the top quintile are the winner-industries, whereas industries in the bottom quintile are the loser-industries. The Long Portfolio is then build using the opaque-losers from the loser-industries. The Short Portfolio is constructed using the opaque-winners from the winner-industries. Using Pastor and Stambaugh (PS, 2003) five-factor model, alphas are estimated for each portfolio and for the difference (the Long-Short return). Monthly alphas are shown in percentages. Observations with stock prices lower than $5 and those for which the absolute difference between forecast value and the true earnings exceeds $10 are excluded. (***), (**), and (*) represent 1%, 5%, and 10% statistical significance respectively.

Panel A - Portfolio Formation Using Last 3 Months							
Holding Period	3 Months	6 Months	9 Months	12 Months	18 Months	24 Months	36 Months
Long	0.515	0.975***	1.216***	1.279***	1.436***	1.459***	1.486***
	(1.365)	(3.209)	(4.411)	(5.287)	(6.606)	(7.111)	(8.378)
Short	1.105***	0.590**	0.547***	0.685***	0.708***	0.743***	0.854***
	(3.646)	(2.483)	(2.697)	(3.249)	(3.502)	(4.120)	(5.468)
Long-Short	0.591	0.384	0.668**	0.593**	0.728***	0.717***	0.633***
	(-1.18)	(1.016)	(2.067)	(2.171)	(2.869)	(3.336)	(3.732)

Panel B - Portfolio Formation Using Last 12 Months							
Holding Period	3 Months	6 Months	9 Months	12 Months	18 Months	24 Months	36 Months
Long	1.236***	0.886***	0.997***	1.078***	1.388***	1.324***	1.397***
	(3.180)	(3.123)	(3.904)	(4.879)	(6.044)	(6.325)	(7.170)
Short	0.817***	0.478**	0.455**	0.513**	0.555***	0.526***	0.577***
	(3.139)	(2.030)	(1.995)	(2.322)	(2.610)	(2.667)	(3.617)
Long-Short	0.418	0.408	0.542	0.565*	0.833**	0.798***	0.819***
	(0.925)	(1.129)	(1.603)	(1.805)	(2.509)	(2.631)	(3.300)

Table 9 – Return Premium due to Excessive Co-movement

This table presents the performance of trading strategies that exploit temporary mispricing of opaque stocks due to excessive co-movement with non-opaque ones. Within each industry (four-digit SIC code), stocks are sorted monthly according to the number of analysts who issued at least one EPS forecast over the last twelve months. Only stocks followed by at least one analyst are included. Stocks into the bottom quintile (considered opaque) are used to form the Long and Short Portfolios (using equal weights). Within each industry, opaque stocks are further sorted and assigned to quintiles according to the cumulated return over the last 3/12/24/36 months (different formation periods are used). Opaque stocks in the top quintile are the opaque-winners, whereas those in the bottom quintile are the opaque-losers. In parallel, industries are sorted monthly according to the cumulated average return of the non-opaque stocks over the last 3/12/24/36 months. Industries in the top quintile are the winner-industries, whereas industries in the bottom quintile are the loser-industries. The Long Portfolio is then build using the opaque-losers from the loser-industries. The Short Portfolio is constructed using the opaque-winners from the winner-industries. Using Pastor and Stambaugh (PS, 2003) five-factor model, alphas are estimated for each portfolio and for the difference (the Long-Short return). Monthly alphas are shown in percentages. Observations with stock prices lower than $5 and those for which the absolute difference between forecast value and the true earnings exceeds $10 are excluded. (***), (**), and (*) represent 1%, 5%, and 10% statistical significance respectively.

Panel C - Portfolio Formation Using Last 24 Months							
Holding Period	3 Months	6 Months	9 Months	12 Months	18 Months	24 Months	36 Months
Long	0.780*	1.131***	1.316***	1.381***	1.368***	1.371***	1.155***
	(1.802)	(3.049)	(4.110)	(4.489)	(5.418)	(5.808)	(4.951)
Short	0.263	0.316	0.332	0.322	0.281	0.243	0.26
	(0.945)	(1.253)	(1.408)	(1.444)	(1.359)	(1.257)	(1.550)
Long-Short	0.517	0.815*	0.984**	1.059***	1.087***	1.128***	0.895***
	(0.975)	(1.758)	(2.407)	(2.655)	(2.994)	(3.353)	(2.985)

Panel D - Portfolio Formation Using Last 36 Months							
Holding Period	3 Months	6 Months	9 Months	12 Months	18 Months	24 Months	36 Months
Long	0.56	0.974**	1.178***	1.169***	1.293***	1.197***	1.230***
	(1.192)	(2.389)	(3.391)	(3.755)	(4.526)	(4.728)	(5.177)
Short	0.081	0.132	0.039	0.086	0.046	0.03	0.17
	(0.334)	(0.577)	(0.182)	(0.409)	(0.225)	(0.154)	(0.951)
Long-Short	0.479	0.842*	1.139***	1.083***	1.246***	1.166***	1.060***
	(0.881)	(1.723)	(2.656)	(2.686)	(3.214)	(3.355)	(3.393)

Figure 1 – BDID in Analyst Coverage

This figure shows the trend of average analyst coverage (per quarter) in the treatment sample net of the control group (in a given quarter) up to four quarter before and after the merger event. Each quarter, benchmark portfolios are constructed using the control sample based on stocks' size (SIZE), book-to-market ratio (BTM), cumulated past quarter's return (MOM) and the number of analysts who issued at least one EPS forecast for the firm over the last twelve months (COVERAGE). The benchmark assignment involves three portfolios in each category. Each stock in the treatment sample is then assigned to (and compared against) its own benchmark SIZE/BTM/MOM/COVERAGE-matched. Dotted lines illustrate 95% confidence intervals.

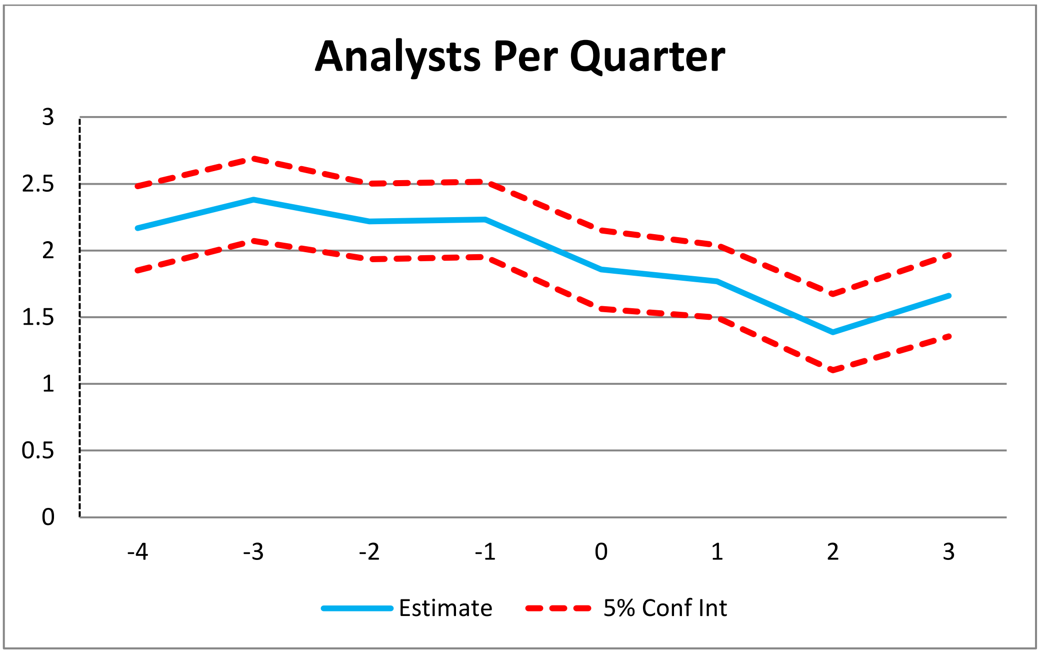


Figure 2 – BDID in Monthly Returns

This figure shows the trend of monthly returns in the treatment sample net of the control group (in a given month) from twelve months before and up to twelve months after the merger event. Each quarter, benchmark portfolios are constructed using the control sample based on stocks' size (SIZE), book-to-market ratio (BTM), cumulated past quarter's return (MOM) and the number of analysts who issued at least one EPS forecast for the firm over the last twelve months (COVERAGE). The benchmark assignment involves three portfolios in each category. Each stock in the treatment sample is then assigned to (and compared against) its own benchmark SIZE/BTM/MOM/COVERAGE-matched. Dotted lines illustrate 95% confidence intervals.

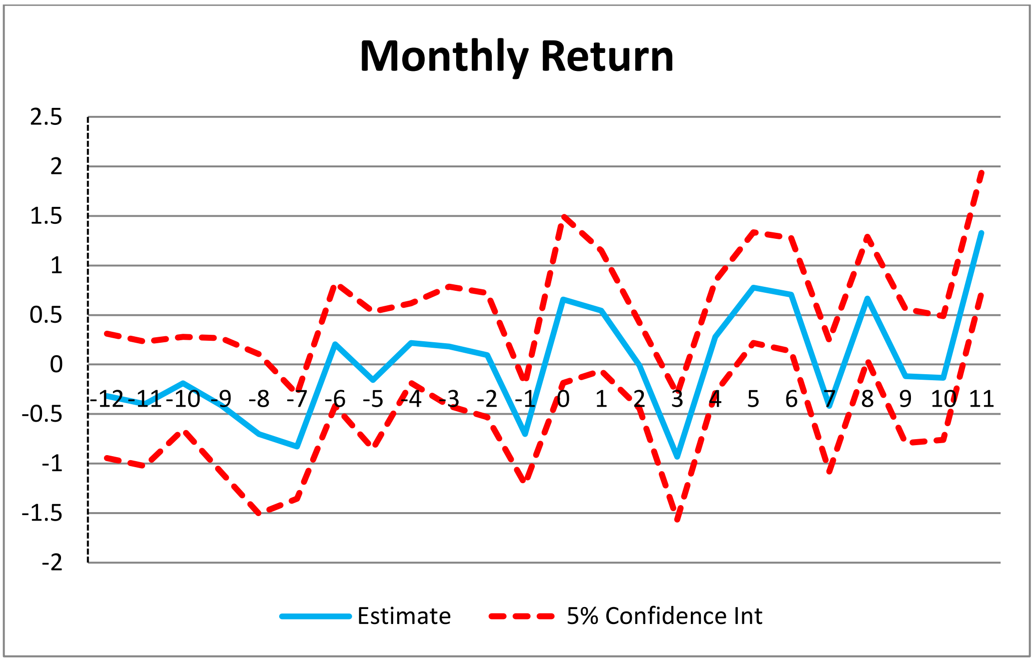


Figure 3 – BDID in Monthly Turnover

This figure shows the trend of monthly turnover in the treatment sample net of the control group (in a given month) from twelve months before and up to twelve months after the merger event. Each quarter, benchmark portfolios are constructed using the control sample based on stocks' size (SIZE), book-to-market ratio (BTM), cumulated past quarter's return (MOM) and the number of analysts who issued at least one EPS forecast for the firm over the last twelve months (COVERAGE). The benchmark assignment involves three portfolios in each category. Each stock in the treatment sample is then assigned to (and compared against) its own benchmark SIZE/BTM/MOM/COVERAGE-matched. Dotted lines illustrate 95% confidence intervals.

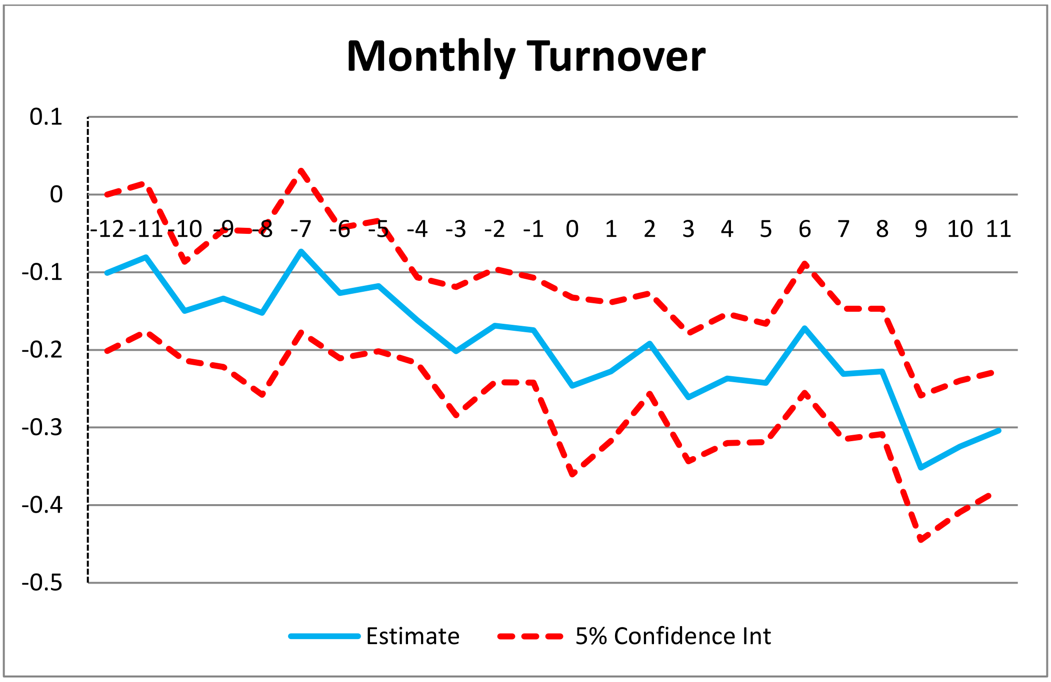


Figure 4 – BDID in Co-movement with an Industry EW Index

This figure shows the trend of intra-quarter levels of correlation across daily returns on an individual stock and an index constructed using every other available stock into the same industry. For each treated stock, I net the level of correlation of the corresponding average level of correlation for the control group (in a given quarter). Each quarter, benchmark portfolios are constructed using the control sample based on stocks' size (SIZE), book-to-market ratio (BTM), cumulated past quarter's return (MOM) and the number of analysts who issued at least one EPS forecast for the firm over the last twelve months (COVERAGE). The benchmark assignment involves three portfolios in each category. Each stock in the treatment sample is then assigned to (and compared against) its own benchmark SIZE/BTM/MOM/COVERAGE-matched. The time window spans from twelve months before up to twelve months after the merger event. Dotted lines illustrate 95% confidence intervals.

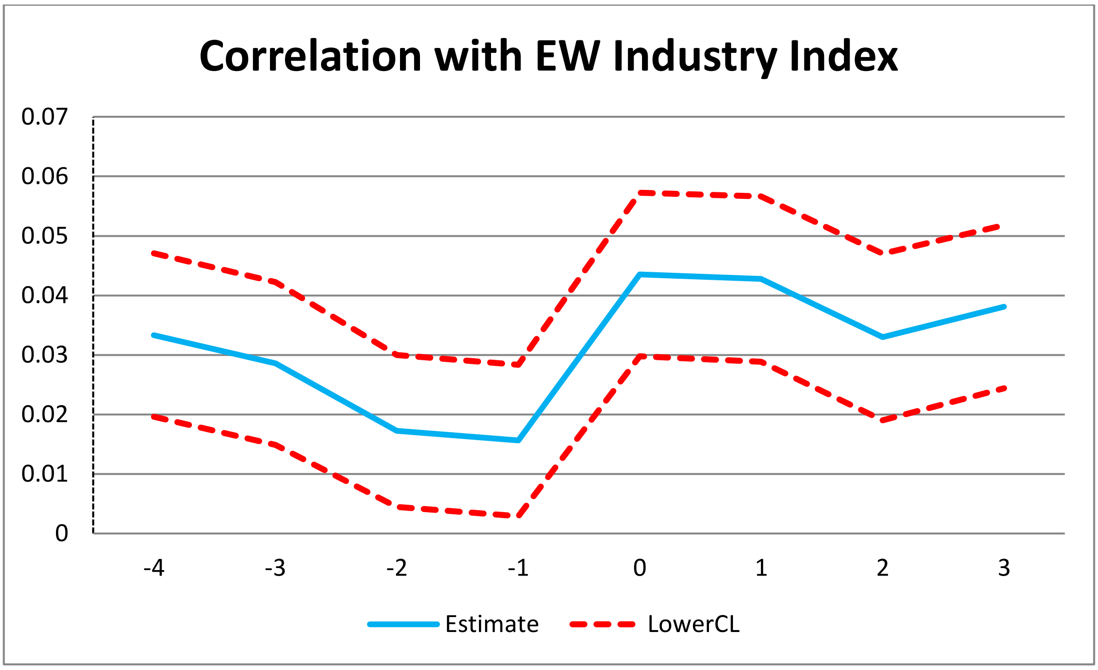


Figure 5 – BDID in Co-movement across Individual Stocks

This figure shows the trend of intra-quarter correlations across daily returns on individual stocks. Instead of raw returns, residuals of Carhart's (1997) four-factor model are used. Levels of correlation displayed are for treated stock-pairs and net of the corresponding average level for control pairs (in a given quarter). Each quarter, benchmark portfolios are constructed using the control sample based on stocks' size (SIZE), book-to-market ratio (BTM), cumulated past quarter's return (MOM) and the number of analysts who issued at least one EPS forecast for the firm over the last twelve months (COVERAGE). The benchmark assignment involves three portfolios in each category. Each stock in each treated pair is then assigned to its own portfolio SIZE/BTM/MOM/COVERAGE-matched. Thus, stocks pairs are compared against benchmarks formed by control pairs where each stock comes from the same benchmark portfolio as one stock in the treated pair. The time window spans from twelve months before up to twelve months after the merger event. Dotted lines illustrate 95% confidence intervals.

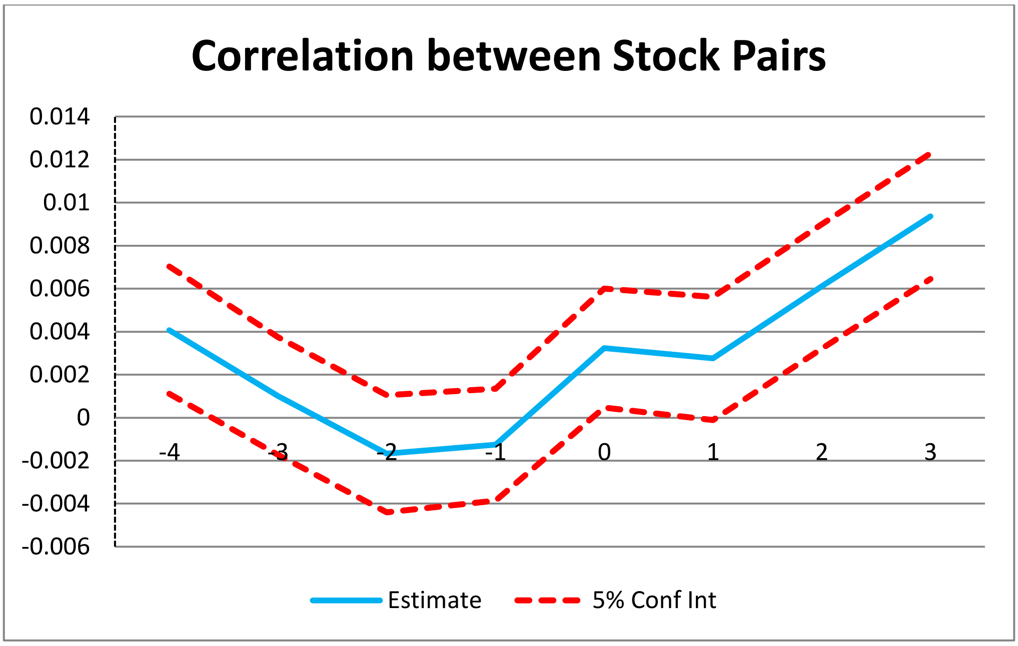
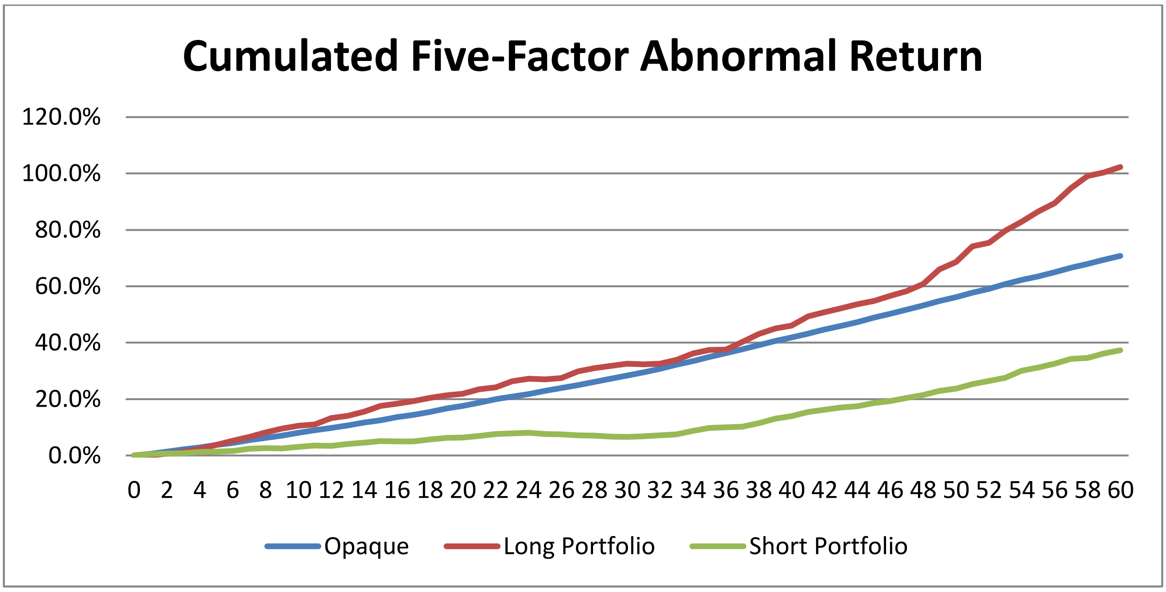


Figure 6 – Five-factors Cumulated Abnormal Return

This figure graphs the abnormal buy-and-hold performance of trading strategy that use portfolios built with opaque stocks. Each month, stocks are sorted according to the number of analysts who issued at least one EPS forecast over the last twelve months. Stocks in the bottom decile (followed by fewer analysts) are used to form the Opaque Portfolios (using equal weights). Opaque stocks are further sorted into five quintiles according to their own cumulative returns over the last 24 months. Stocks in the top quintile are the opaque-winner, while those in the bottom quintile are the opaque losers. The industries to which these stocks belong are then independently sorted into five quintiles according to the average cumulated return of the non-opaque stocks. Industries in the top quintiles are into their industries. Stocks in the top quintile are the winner-industries, while those in the bottom quintile are the loser-industries. The Long Portfolio buys the opaque-losers into the loser-industries, and the Short Portfolio buys the opaque-winners into the winner-industries (both portfolios use equal weights). Using Pastor and Stambaugh's (PS, 2003) five-factor model, alphas are estimated for each portfolio and for the portfolio that goes long on the opaque stocks. Alphas are shown in percentages.



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