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INFORMATION UNCERTAINTY AND THE REACTION OF STOCK PRICES TO NEWS

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Abstract

Recent theoretical papers suggest that high uncertainty about firms' economic prospects can explain delays in the adjustment of their stock prices to economic news. Using analyst forecast revisions and earnings announcements as proxies of news, we find mixed evidence in support of this hypothesis. We confirm that stocks of firms whose prospects are highly uncertain display a relatively large delayed price reaction (so-called continuation) after the release of news, but we argue that this evidence does not necessarily imply a slower adjustment speed. Indeed, for these stocks the immediate reaction to news is also relatively strong. In fact, the magnitude of the delayed price reaction (the price continuation) depends both on the degree of price sluggishness and on the "scale" of the news hitting the stock. We therefore consider both the delayed and immediate responses, and compute measures of adjustment speed that do not depend on the "scale" of the news. We then compare these measures across portfolios of stocks characterized by different degrees of uncertainty. Our findings indicate that: (i) stock prices characterized by high uncertainty tend to adjust to bad news more sluggishly than those characterized by low uncertainty; (ii) the opposite holds true in the case of good news; (iii) stock prices characterized by high uncertainty tend to adjust to bad news more sluggishly than to good news. Previous empirical literature focuses on price continuation patterns but neglects to control for the "scale" of the news, reaching erroneous conclusions.

JEL Classification: G11, G14.
Keywords: stock price continuation, price adjustment speed, news, earnings announcements, analysts' forecasts, post-earnings announcement drift, post-analyst forecast revisions drift, managers' incentives.

Contents

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* Bank of Italy, Economics, Research and International Relations.

1. Introduction

Over the last 20 years, a large literature has documented price continuation anomalies in the stock market, i.e. that future stock returns are predictable based on information that is public at a certain date, and should therefore have already been incorporated into prices. Among the best-documented instances of price continuation are the post-earnings announcement drift (Bernard and Thomas (1989, 1990)), the post-analyst forecast revisions price drift (Stickel (1991); Gleason and Lee (2003)), and momentum (Jegadeesh and Titman (1993), (2001); Chan, Jegadeesh and Lakonishok (1996)).

Investors' underreaction to new information is one common explanation for these patterns: new information may take time to work its way into stock prices, giving rise to lagged adjustment. One prominent strand of the literature that has tried to rigorously model underreaction to news relies on behavioral theories, which posit that investors suffer from some form of irrationality (see Thaler (1993)). Cognitive biases such as conservatism or overconfidence, well documented in the psychology literature, have been incorporated into formal models yielding underreaction patterns.[1] Some of these theories imply that psychological biases should be stronger when there is more uncertainty about a stock's value (see in particular Hong and Stein (1999), Daniel, Hirshleifer and Subrahmaniam (2001)). In his survey of this literature, Hirshleifer (2001) summarizes the point as follows: "greater

[1] In Barberis, Shleifer and Vishny (1998) conservative investors tend to change their opinions too slowly, generating underreaction to news. Daniel, Hirshleifer and Subrahmaniam (1998, 2001) build on investors' overconfidence in their private signals (the belief that the signal is more precise than it really is): overconfidence causes investors to underweight public information as it is released, so that this information will take a relatively long time to work its way into the stock price. In Hong and Stein (1999) underreaction stems from the gradual diffusion of private information across the population of investors. These theories also try to explain longer term overreaction, another well documented stock price anomaly. We overlook this aspect because, as we discuss below, our focus is on testing the implications of these theories for the hypothesis that stock prices underreact to new information in the short-term.

uncertainty about a set of stocks … leaves more room for psychological biases. At the extreme, it is relatively hard to misperceive an asset that is nearly risk-free" (p. 1575).[2]

Some recent empirical papers have tried to test this a priori. Zhang (2006) argues that if investors underreact to new information due to psychological biases, and if such biases are stronger when there is uncertainty about a firm's value, then underreaction patterns will be stronger for stocks of firms characterized by greater uncertainty. To test this claim, he partitions his sample of US stocks into a high and a low uncertainty group (according to various uncertainty proxies), and shows that the former group is characterized by relatively high price continuation. Zhang interprets his finding as supporting the hypothesis that slow price adjustment reflects investor underreaction to new information due to psychological biases. Other authors reach similar conclusions. For instance, Hong, Lim and Stein (2000) find that momentum is stronger for the shares of firms characterized by small size or low (residual) analysts coverage (uncertainty proxies similar to those used by Zhang (2006)), and interpret this as evidence that momentum reflects the gradual diffusion of information about high uncertainty firms across investors.[3]

In this paper we propose a sharper test of the hypothesis that the price adjustment to economic news is slower for stocks of high uncertainty firms, and present new evidence on the issue. The above papers focus on price continuation phenomena, i.e. on the magnitude of the delayed stock price reaction to news. This focus is interesting per se, and is coherent with

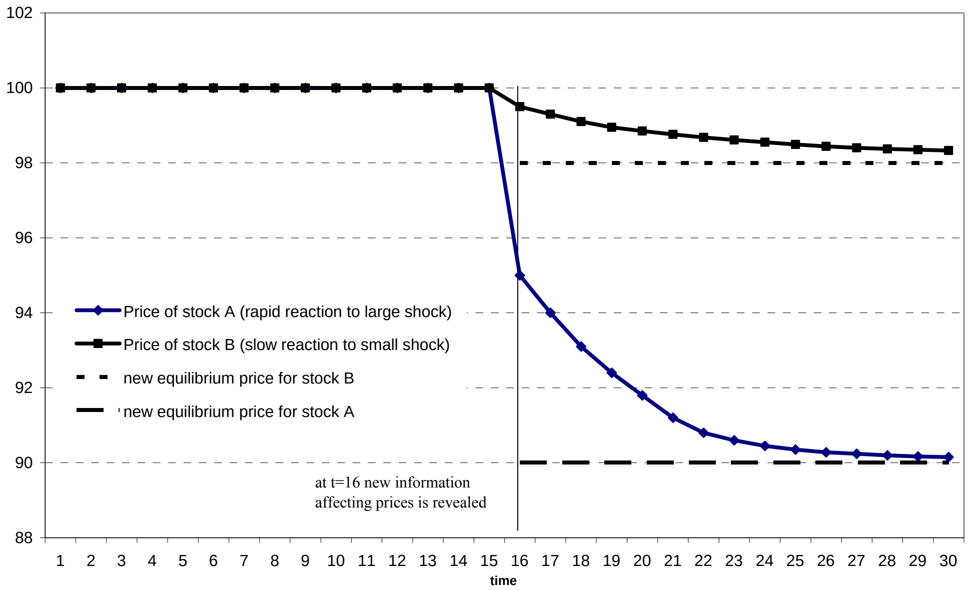
[2] Alternative theories trying to explain stock price anomalies assume rational investors subject to uncertainty (see e.g. Brav and Heaton (2002) and the references therein). The idea is that in the presence of uncertainty Bayesian investors will face a signal extraction problem, which will cause new information to affect prices gradually. A recent strand focuses on investors' rational inattention: as information processing is costly, investors may overlook economic news (Huang and Liu (2007)), take time to learn their information content (Peng (2005), Peng and Xiong (2006)), or be distracted (DellaVigna and Pollet (2009), Hirshleifer, Lim and Teoh (2007)).

[3] In these papers, as in ours, information uncertainty means that new information has uncertain implications for a firm's value, without distinguishing whether this is due to the volatility of a firm's underlying fundamentals, or to poor information on the firm itself (opacity).

the definition of underreaction commonly adopted in the literature, i.e. that good (bad) future stock returns can be predicted from good (bad) past performance.[4] However this definition, and the focus on price continuation, can be misleading when the purpose of the analysis is to compare underreaction patterns across groups of stocks with different characteristics, as in our case.

Our basic point is that the magnitude of the delayed price reaction (the price continuation) depends both on the degree of price sluggishness *and* on the "dimension" of the news hitting the stock, and is therefore, in principle, uninformative about the adjustment speed. Telling which class of stocks adjusts to news more rapidly requires a "scale-free" measure, i.e. one that is independent of the dimension of the news. To this end, both the immediate and the delayed stock price reaction to the news must be considered. An example may help clarify this point.

Fig. 1: Stock prices reaction to the arrival of bad news: large price continuation need not imply slow price adjustment



[4] This definition is taken from Brav and Heaton (2002). Barberis, Shleifer and Vishny (1998), Zhang (2006) adopt a similar one.

Consider two stocks (or portfolios of stocks), A and B, and suppose that the price of stock A reacts in a relatively rapid fashion to news, whereas B is more sluggish, due e.g. to informational opacity. Suppose that at a certain date both stocks are "hit" by unexpected bad news. However, for stock A the news is particularly bad, whereas for B it is only moderately negative, so the price adjustment is large for A, from 100 to 90, and small for B, from 100 to 98. Figure 1 reports the two price responses.[5] By assumption, the price of B will move slowly to the new equilibrium: one quarter of the adjustment (-0.5 percent in terms of returns) takes place on date 16, when the news is released, the remaining three quarters (an additional -1.5 percent) in subsequent periods. The price of A instead moves relatively fast: half of the adjustment (-5.0 percent) is immediate and half is delayed. The point of the example is that, looking only at the delayed price response, one could conclude that underreaction is stronger for stock A (-5.0 percent is larger in absolute value than -1.5 percent) in spite that its price is less sluggish by assumption.

Summing up, to test whether the price of stock A underreacts to news more than that of stock B, one must measure their adjustment speed. An intuitive way to control for the size of the surprise, suggested by the figure, is to take the ratio between the delayed and the immediate returns. In a nutshell, this is what we do: we compute and compare several alternative estimators of stock price adjustment speed across portfolios of stocks characterized by different degrees of uncertainty.

It is worth noting that the methodological point illustrated in figure 1 is quite general. It holds regardless of whether the slow reaction of stock prices to news reflects cognitive biases or other causes, e.g. rational behavior under uncertainty, and it applies whenever the purpose of the analysis is to compare price reaction patterns across different groups of stocks.

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5 The figure reports fictitious data to illustrate the example discussed in the text. Similar curves are derived in various theoretical models (see e.g. Daniel, Hirshleifer and Subrahmaniam (1998), Brav and Heaton (2002)).

To test the hypothesis that the price adjustment to economic news is slower for stocks of high uncertainty firms, we consider two types of news, corresponding to the two above-mentioned instances of price continuation: the post-analyst revisions price drift and the post-earnings announcement drift (PEAD). In the first case, the news is the revision of analyst earnings forecasts; in the second, the release of quarterly earnings. In either case, we proceed as follows: we partition stocks into a "good news" and a "bad news" group; we sort each group in ascending order of uncertainty, using several proxies of uncertainty; for each news group, we compare the stock price adjustment speed of high versus low uncertainty stocks.

The exercises focusing on the post-analyst revisions price drift are interesting in their own right, and because they allow us to clearly contrast our results to those in Zhang (2006). However, the underlying dataset does not readily lend itself to measuring news arrival and stock price reaction with precision, as analyst forecasts revisions are computed on a monthly basis. Our second set of exercises is based on the PEAD anomaly, probably the hardest to reconcile with market rationality (Fama (1998)). In this case, knowledge of the day of the actual quarterly earnings release allows us to compute more precise measures of the immediate and delayed stock price reaction to news, and hence of price sluggishness. In spite of these differences, the exercises performed on the two datasets deliver broadly coherent results.

Overall, our evidence offers only partial support to the thesis that the prices of high uncertainty stocks are relatively more sluggish. In a nutshell, we find that while the speed with which the prices of high uncertainty stocks adjust to *bad* news is equal or lower than that of low uncertainty stocks, as suggested by the theories summarized above, the opposite finding holds true in the case of good news. Moreover, there is strong evidence that the prices of high uncertainty stocks adjust more slowly to bad news than to good news. These results may help to discriminate among alternative explanations of the underreaction hypothesis. In particular, we discuss our findings in the context of theories of short-sale constraints and of managers incentives and discretion.

Our results also cast new light on price continuation patterns. In the case of negative quarterly earnings surprises, price continuation is observed both among low and high uncertainty stocks, and it is stronger among the latter, confirming existing results. When good news are considered, price continuation for high uncertainty stocks is found to be lower, equal or higher than that for low uncertainty stocks, depending on the proxy of uncertainty, or of news.

Our paper is related methodologically to recent papers studying the PEAD. Hirshleifer, Lim and Teoh (2007) and DellaVigna and Pollet (2009) test the hypothesis that the price adjustment following earning announcements is more sluggish if investors are "distracted". They divide stocks into two groups, depending on whether their announcements take place on "normal" days or on "high distraction" days, and compare the immediate vs. delayed price reaction, similarly to what we do below. In the former paper, "high distraction" days are those featuring a great number of earnings announcements, which compete for investors' limited attention; in the latter they are Fridays, when investors are distracted by the perspective of the week-end. Both papers show that on "normal" days the stock price adjustment is faster, and the drift is smaller, relative to "high distraction" days.

The next section presents the testing strategy in detail, justifies our use of four alternative measures of adjustment speed, and discusses some important methodological aspects. Section 3 illustrates our two main datasets. Sections 4 and 5 report the bulk of the empirical analysis, mainly focusing on the high vs. low uncertainty cut, whereas section 6 describes the bad vs. good news dimension of our results. In section 7 we summarize the main findings and discuss their economic interpretation. Section 8 concludes.

2. Testing strategy

In this section we describe the methodology which we apply, with small adaptations, to the two well-known instances of price continuation mentioned above: the post-analyst forecast revisions price drift and the post-earnings announcement drift (PEAD), analyzed in sections 4 and 5, respectively.

We denote by S_T^j the news hitting stock *j* at time *T*. We measure the immediate reaction to S_T^j by the stock's abnormal return around the announcement of the news, r_T^j, and the delayed reaction by the abnormal return in the following period, r_{T+d}^j.[6] To compare the speed with which the stock prices of firms characterized by different degrees of informational opacity react to news we proceed as follows. In each period *T* we partition stocks into 3 groups, depending on whether S_T^j is positive, zero or negative. Within the positive and negative groups we then sort stocks into 5 quintiles, based on several proxies for information uncertainty (to be described below), one at the time. We replicate the procedure for each period, and compute our adjustment speed estimators for the four relevant portfolios (bad vs. good news, high vs. low uncertainty) over the available sample period.[7] We add uppercase superscripts to denote uncertainty and news types portfolios, so that $r_T^{j,U,N}$, say, denotes the immediate abnormal return for stock *j* belonging to the first (*U*=*L*) or the fifth (*U*=*H*) uncertainty quintile, in either the bad news (*N*=*B*) or good news (*N*=*G*) portfolios. We omit superscripts whenever not necessary.

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6 Throughout the paper we use abnormal returns, in the tradition of the literature on event studies. The idea is that using delayed and current returns to make inference on stock price sluggishness makes sense only if returns measure the actual reaction to the news, correcting for possible risk premia and predictable components.

7 The results presented below remain virtually unchanged if the order of the sorts is reversed – i.e. if uncertainty quintiles are computed first.

We begin by checking the magnitude of the immediate and delayed price reactions for these portfolios. Consider the good news portfolios (the reasoning for the bad news is symmetric), and suppose we observe $mean(r_T^{j,L}) > mean(r_T^{j,H}) \geq 0$ and $mean(r_{T+d}^{j,H}) > mean(r_{T+d}^{j,L}) \geq 0$. This can be seen as first evidence that the prices of high uncertainty stocks are more sluggish than those of low uncertainty stocks. However, simply looking at these sample means does not allow us to say whether the adjustment speeds of the two portfolios are statistically different; all the more so if the first inequality is replaced by $mean(r_T^{j,H}) > mean(r_T^{j,L}) \geq 0$, a case we often encounter in the empirical analysis below. What we need is a synthetic measure of price sluggishness and a joint test of the two inequalities. A natural measure of sluggishness is given by ρ in the following expression:

(1) $$\rho^{U,N} = mean(r_{T+d}^{j,U,N}) / mean(r_T^{j,U,N}), \qquad U = L, H;\ N=B, G.$$

Note that ρ measures the magnitude of the delayed return relative to that of the immediate return, doing away with the potential problem illustrated in figure 1.[8] The case ρ=0 corresponds to a pure random walk hypothesis, i.e. to market efficiency, and to infinite price adjustment speed. If ρ>0 there is price continuation; the larger the value of the statistic, the slower the adjustment. Finally, ρ<0 entails price overreaction/reversal.[9]

A potential drawback of the mean estimator (1) is that it could be hiding asymmetries in the distributions of individual stock price reactions within the various portfolios. Consider

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8 Similar measures are used by Masulis and Shivakumar (2002), DellaVigna and Pollet (2009). For each of the two portfolios whose adjustment speed they compare, they compute a ratio that, in our notation, can be written as $mean(r_{T+d}^j)/[mean(r_T^j)+mean(r_{T+d}^j)]$.

9 For the estimator ρ^U to be a good measure of adjustment speed, r_T^j must be a good measure of the stock price reaction to the arrival of news; no other surprise should hit the stock during the adjustment period, i.e. from *T* to *T*+*d*; the adjustment must be completed by *T*+*d*. In the empirical work presented below some of these conditions may not be met, so we modify our setup in various ways to check the robustness of our results.

e.g. the good news, high uncertainty portfolio, and suppose that r^j_{T+d} has a zero mean binomial distribution, say r^j_{T+d} = -0.9 with probability 0.1, and 0.1 with probability 0.9. In this case estimator (1) would correctly yield ρ^H= 0, yet 90 percent of the stocks would display some price sluggishness. While the example is clearly ad hoc, it illustrates the concrete possibility that estimator (1) delivers a message which does not reflect the behavior of the majority of individual stocks in a portfolio.

To control for this possibility and gain additional insights on the phenomenon, we also compute three other measures of price sluggishness. The first is the share of stocks displaying price continuation within each portfolio, i.e. the percentage of stocks whose price in period *T*+1 moves in the same direction as in *T*, provided that the move in *T* is coherent with the sign of the surprise. For brevity, we shall refer to this statistic as the "share":

(2) $$Share^{U,N} = \text{prob}[sign(r^{j,U,N}_{T+d})=sign(r^{j,U.N}_{T}) | sign(r^{j,U,N}_{T})=sign(S^{j,U,N}_{T})],$$

$$U = L, H;\ \ N=B, G.$$

This statistic would be equal to 0.9 in the case of the above example, correctly signaling an asymmetric distribution of r^j_{T+d}, whereas it would yield a message analogous to that of estimator (1) if the distribution were symmetric.[10] Indeed, whereas (1) may be affected by asymmetries in the numerator as well as in the denominator, the share is immune from this problem.

One drawback of the "share" is that it does not yield a direct measure of adjustment speed. Thus, we also compute the following two additional median-based estimators of $\rho^{U,N}$:

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[10] This statistic is related to the early tests of the random walk hypothesis, which compared the frequency of sequences (pairs of consecutive returns with the same sign) with that of reversals (pairs of consecutive returns with opposite signs) in historical stock returns. See Campbell, Lo and MacKinlay (1997).

(3) $$\rho^{U,N} = median(r_{T+d}^{j,U,N}) / median(r_T^{j,U,N})$$

$$U = L, H; N = B, G.$$

(4) $$\rho^{U,N} = median(r_{T+d}^{j,U,N} / r_T^{j,U,N}),$$

Used in conjunction with the "share", these estimators are suitable to capture asymmetries in the distribution of r_{T+d}^j. We shall see that these asymmetries do emerge from the data, raising the issue of which measure of adjustment speed – mean-based vs. median-based – one should eventually favor and draw conclusions upon.

In practice, estimators (1)-(4) and the related standard errors are computed as follows. The ratio of means in (1) is obtained by taking averages of the numerator and denominator over the pooled cross-section-time series dataset for each portfolio (high vs. low uncertainty, bad vs. good news). To test for equality of the ρs across the various portfolios, we first compute the ratio r_{T+d}^j / r_T^j for each stock and time period *T*. Next, we arrange the data in a panel and regress this ratio on four zero-one portfolio dummies. We use a weighted regression, in which each observation is weighted by r_T^j scaled by the sum of r_T^j across all *j*. This ensures that the regression coefficients equal the ρ obtained as in (1). The standard errors are adjusted for clustering at the date level. The "shares" in (2) are obtained as follows. First, shares are calculated for each portfolio and time period using a relative frequency approach, obtaining a time series for each portfolio. The four time series are then stacked in a panel and regressed on the usual four zero-one portfolio dummies. The estimated "shares" are the coefficients from these regressions; the related standard errors are adjusted for heteroskedasticity. The ratio of medians (3) and its standard error are obtained via an analogous regression. To derive the median of ratios (4) we first compute the ratio r_{T+d}^j / r_T^j for each stock, obtaining a time series for each stock. The time series are then stacked in a panel and regressed on the usual four zero-one portfolio dummies. We use a quantile regression, which ensures that the dummy coefficients are equal to the median of the individual ratios computed over the pooled cross section-time series data for each portfolio.

3. Data

Our two datasets are derived from three main sources: CRSP for returns, Compustat for quarterly balance sheet and income statement data, and I/B/E/S for analyst forecasts on quarterly earnings per share. The sample period goes from January 1985 to the end of 2005. Data relate to companies with ordinary shares quoted on the NYSE, AMEX and Nasdaq. We use all sectors and consider only ordinary shares (i.e. we exclude American Depository Receipts and Exchange Traded Funds). All measures of analyst forecasts were computed from the unadjusted detailed history I/B/E/S dataset. This method avoids a rounding bias which has previously been noted to affect I/B/E/S final adjusted statistics (see e.g. Diether, Malloy and Scherbina (2002)). Following Zhang (2006), we dropped all observations for which the forecast revision, or the forecast error, was larger, in absolute value, than the stock price at the end of the previous year. In addition, to eliminate illiquid stocks and stocks of newly quoted companies (possibly IPOs), we dropped observations for which the price was lower than 5 US dollars or the age of the company (measured with the time since first CRSP quotation) was less than one year.

The dataset on the post-analyst revisions price drift, used in section 4, comprises the following variables. $FOR^{j}_{T,\tau}$, expressed in current dollars, is the simple average of the forecasts of quarter τ earnings per share released by the various analysts covering the stock during month T (source: I/B/E/S). The baseline results presented below are derived by defining news as $S^{j}_{T,\tau} = (FOR^{j}_{T,\tau} - FOR^{j}_{T-1,\tau}) / P^{j}_{T-1}$, the revision in analyst forecast between the end of month T and the end of month T-1 (computed on a balanced panel of analysts), normalized by the stock's lagged price. The forecasts are adjusted to eliminate the rounding error previously described, and stale forecasts (defined as those not confirmed by the analyst during month *T*) are discarded. When actual earnings data relating to a given quarter are published, the focus shifts to the next quarter, and the news is redefined as $S^j_{T,\tau+1}$. In the analysis we overlook the fact that, as *T* increases, the length of the forecasting horizon declines. Accordingly, we omit the τ subscript. We adopt the following six commonly used proxies of information uncertainty, defined so that larger values denote higher uncertainty levels. $1/MV^j_T$ is the reciprocal of market capitalization of the firm at the end of month *T*, in million of dollars. $1/COV^j_T$, is the reciprocal of the total number of analysts who covered the company at least once during the previous year. $1/AGE^j_T$ is the reciprocal of the firm's age, measured by the number of years that the firm has been present in the CRSP dataset. $SIGMA^j_T$ is the standard deviation of weekly (Thursday to Wednesday) excess returns computed over the 52 weeks ending in month *T*. $CVOL^j_T$ is the standard deviation of the ratio of operative income (Compustat #21) over average total assets (Compustat #44), computed over 20 quarters (where unavailable, over a minimum of 8 quarters).[11] $DISP^j_T$ is the standard deviation of valid analyst forecasts at the end of month *T*, scaled by the stock price at the end of the previous year (source: I/B/E/S).

The concept of uncertainty we refer to is investors' subjective uncertainty about the true value of a stock, regardless of what determines it. This uncertainty could be caused by an intrinsic characteristics of the firm, e.g. high cash-flows volatility, or by incentive-driven motivations, e.g. investors' low level of attention for small firm stocks, or the firm's manager

[11] The operative income series was seasonally adjusted by taking the difference between values in the current quarter and the corresponding quarter of the previous year. The results obtained using this uncertainty proxy relate to non-banks only, due to data availability problems.

choice of the degree of opaqueness. Reliance on several proxies aims to capture different aspects of information uncertainty, as well as the possibility that each proxy might capture things other than uncertainty. For example, firm size and analyst coverage are also commonly used to proxy for investor recognition in the literature that examines delays in price adjustment due to "neglected firm" effects, a concept related to our definition of information uncertainty (see e.g. Hou and Moskowitz (2005)). Moreover, proxies of uncertainty such as market capitalization tend also to be related to (and are often used as an indicator of) stock liquidity. Since liquidity, or the presence of short-selling constraints, might induce price sluggishness, driving our results independently of uncertainty, this is a factor we shall try to control for in our analysis. A word of caveat is also warranted for $DISP_T^j$, the dispersion in analyst forecasts. This proxy cannot be computed for firms with one or no analyst coverage which, as just mentioned, are likely to be small, opaque, "neglected-type" ones. We refer to Zhang (2006) for a more detailed discussion of these proxies and of their use in previous literature.

The immediate abnormal return of stock *j* in month *T*, denoted by r_T^j, is computed as the percentage month-on-month change in the dividend-adjusted price minus the market return in the same month, computed using the value-weighted CRSP index. Stock prices are measured at month-end, in current dollars. The delayed abnormal return, denoted r_{T+d}^j, is computed by compounding monthly returns over the following *d* months (our baseline results are derived using $d = 1$, but we analyze different values in the robustness checks section).

This dataset has a monthly frequency and totals about 590,000 observations, resulting from about 2,400 firms on average in the cross-section and 21 years of data. Summary statistics for the main variables are reported in table 1, panel A.

Table 1 - Descriptive Statistics

In panel A returns are computed as monthly buy and hold returns, in panel B as cumulative returns in the 3-day window around the earnings data release. *MV* is market capitalization. *COV* is the number of analysts covering the stock. *AGE* is measured by the number of years that the firm has been present in the CRSP dataset. *SIGMA*, *CVOL* and *DISP* measure the volatility of weekly returns, the volatility of income, and the dispersion of analyst forecasts, in the order. See section 3 for details. Panel A refers to monthly observations; panel B to quarterly observations indexed to the time of earnings releases. In both panels the sample period is January 1985-December 2005.

	No. obs.	Mean	Std Dev	Min	Max	Q1	Median	Q4
Panel A: Analyst forecasts revisions dataset (monthly frequency)								
Returns (%)	592,045	1.8	14.3	-84.8	937.4	-5.3	1.1	7.8
MV ($ million)	592,045	2,995	13,147	3	602,433	170	499	1,653
COV (n. analysts)	592,045	16.4	16.5	1.0	79.9	4.5	10.8	22.7
AGE (years)	576,312	9.1	7.7	1.0	63.0	4.0	7.0	12.0
SIGMA (%)	590,336	5.7	3.0	1.1	34.5	3.6	5.0	7.1
CVOL (%)	367,599	1.6	2.4	0.0	128.2	0.5	1.0	1.9
DISP (%)	427,000	0.3	9.6	0.0	4291.4	0.0	0.1	0.2
Panel B: Post-earnings announcements (PEAD) dataset (quarterly frequency)								
Returns (%)	201,859	0.3	7.7	-85.6	93.0	-2.9	0.0	3.6
MV ($ million)	201,859	2,853	12,912	4	579,242	158	463	1,524
COV (n. analysts)	201,859	16.4	16.4	1.0	79.9	4.5	10.8	22.7
AGE (years)	196,658	8.8	7.6	1.0	63.0	3.0	6.0	12.0
SIGMA (%)	199,846	5.7	3.0	1.1	32.8	3.6	5.0	7.1
CVOL (%)	125,462	1.6	2.4	0.0	105.7	0.5	1.0	1.9
DISP (%)	161,705	0.4	14.4	0.0	4291.4	0.0	0.1	0.2

The dataset used in section 5 to study the post-earnings announcement drift is similar, except for the following aspects. First, abnormal returns are computed using the market model, as described in section 5. Second, the measures of news $S^j_{T,\tau}$, to be described below, rely on quarterly earnings releases. This yields a quarterly dataset, where all stocks experiencing an earnings release during a given quarter are pooled together in a single cross-section. Accordingly, with a slight change of notation relative to the previous dataset, $r^j_{T-1,T+1}$ denotes the immediate cumulative abnormal return computed over the three-day window surrounding the announcement day *T*. The delayed return, denoted $r^j_{T+2,T+d}$, is computed in an analogous fashion over the following *d* days.

The baseline definition of $S^j_{T,\tau}$ relies on the sign of the stock price immediate abnormal return: an $r^j_{T-1,T+1}$ greater than 0.5 percent is taken to signal a reaction to a piece of good news; vice-versa, stocks with $r^j_{T-1,T+1}$ less than -0.5 percent are assigned to the bad news portfolios. As an alternative measure of news we also use $S^j_{T,\tau} = (EPS^j_{T,\tau} - FOR^j_{T,\tau})/P^j_T$, where $EPS^j_{T,\tau}$ denotes the earnings per share in quarter τ released on day *T* (source Compustat), and $FOR^j_{T,\tau}$ is the average analyst forecast, obtained as a simple average of forecasts in the 30-day period ending on day *T*-1 (source: I/B/E/S; stale quotes were discarded before computing the averages).[12] The uncertainty proxies are computed as illustrated above, except that now $1/MV^j_T$, $SIGMA^j_T$ and $CVOL^j_T$ are computed over the month preceding the earnings release, while $DISP^j_T$ refers to the 30-days period before day *T*-2. Table 1.B presents descriptive statistics for this dataset. The number of observations is considerably lower than that in panel A, reflecting the lower frequency of the data.

Finally, the Fama-French factors, the momentum factor and the risk-free rate used in section 4.4 are obtained from the Fama-French database.

4. Uncertainty and the post-analyst forecast revisions price drift

In this section we evaluate how rapidly stock prices adjust to analyst forecasts revisions. In this context, immediate returns r^j_T and delayed returns r^j_{T+d} are computed on a

[12] DellaVigna and Pollet (2009) note that Compustat and I/B/E/S announcement dates do not always agree, and that before January 1, 1990 both sources report the Wall Street Journal publication date, which is the day following the earnings release. They also mention that after 1994 the quality of the dates is almost perfect.

monthly basis (T and d denote months) and S_T^j is the revision of the average analyst forecast of earnings per share for stock j in month T. Each month T, stocks with positive news (S_T^j >0) are sorted into 5 quintiles, based on our proxies for information uncertainty, one at the time. We replicate the procedure for each month in our sample, and compute relevant statistics over the available sample period (1985-2005). We repeat these steps for the bad news (S_T^j <0) group.

Before moving to the results, we need to clarify a few methodological aspects characterizing this section. First, abnormal returns are computed using the widely-used market-adjusted model (see e.g. Brown and Warner (1985), Conrad, Cornell and Landsman (2002), Chang, Cheng and Yu (2007)): we take the difference between the return of the event firms (those in the bad news, low uncertainty group, say) and the return of the value-weighted market portfolio. In subsection 4.4 we adopt a factor model. Second, we deem r_T^j "immediate" returns because they are computed over the same period as S_T^j. This choice has certain drawbacks. In particular, to gauge the impact of a certain event of interest on the stock price, the literature on event studies focuses on much narrower windows around the event itself, to minimize confounding factors and to avoid overlapping between periods of news and periods of no news. We believe our choice may be justified in the light of our primary intent in this section, which is to maximize the comparability of our results with previous results on price continuation. The robustness checks described in subsection 4.5, and the results in section 5, where the news considered are quarterly earnings releases, give us confidence that these confounding factors are not the main drivers of our findings.

Third, our baseline results are based on stocks whose immediate reaction is in line with the news. Specifically, among the bad news stocks (recording downward analyst forecasts revision) we consider only those characterized by $r_T^j \leq 0$, and drop observations displaying r_T^j>0. Likewise, we drop the observations characterized by r_T^j<0 from the good news groups. This exclusion is warranted by the fact that measuring price continuation and adjustment speed in reaction to a piece of news makes sense only if stock prices display a sensible reaction to the news to begin with. Observations failing to meet this condition are likely affected by noise, or may reflect poor quality of the proxy for news;[13] they should wash out when ρ is estimated as a ratio of means, but they might distort the estimators based on individual stock ratios.[14] Be that as it may, in what follows we check the robustness of our results to this exclusion.

4.1 Behavior of immediate and delayed abnormal returns

Panel A of table 2 reports average abnormal returns in the month following the forecast revision (r_{T+d}^U, d=1). Two main results emerge from the table. First, good news (an improvement in analyst earnings forecasts over a given month) tend to be associated with better-than-average stock performance in the next month; the opposite is true in the case of a downward revision in forecasts. Second, such continuation effect is stronger in the case of high uncertainty stocks. Based on e.g. the first uncertainty proxy, 1/*MV*, a zero-cost portfolio constructed with stocks in the first uncertainty quintile, taking each month a long position in the good news stocks and a short position in the bad news stocks, yields a return of 0.36 percent in the following month. This compares with 2.43 percent for a similar portfolio constructed using stocks in the fifth uncertainty quintile.

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13 Stocks displaying a r_T^j inconsistent with their S_T^j group are a large share of the total (40-45 percent of both the S_T^j>0 or the S_T^j<0 group). Similar figures are found for the dataset in section 5 when S_T^j is defined as actual quarterly earnings per share minus the average of forecasts formulated by analyst in the previous month. Loh and Stulz (2009) find that the stock price reaction to individual analysts forecast revisions is consistent with the sign of the revision in only one third of the cases.

14 Suppose that following e.g. good news the price of stock *j* declines for unobserved reasons, and that a further decline is observed in the following period. Then the ratio r_{T+d}^j / r_T^j, and therefore ρ^j, will be positive, signaling price continuation, whereas the price movements have arguably little to do with the news.

Table 2 - Average abnormal stock returns and information uncertainty
News: analyst forecast revisions

(percentage values; t statistics in italics)

Bad and good news portfolios are constructed based on the revision of the monthly average analyst forecast. Abnormal returns are computed as the return of each stock minus that of the value-weighted market portfolio. The Qs denote uncertainty quintiles. For each month *T* in the sample we partition stocks into 3 groups, depending on whether the forecast revision in *T* is positive, zero or negative. Within the positive and negative forecast revision groups we then sort stocks into 5 quintiles, based on six proxies for information uncertainty measured in *T*, and compute average returns for each quintile over the 1985-2005 period. Panels A and B report returns in *T*+1; and in *T*, in the order. *MV* is market capitalization. *COV* is the number of analysts covering the stock. *AGE* is measured by the number of years that the firm has been present in the CRSP dataset. *SIGMA*, *CVOL* and *DISP* measure the volatility of weekly returns, the volatility of income, and the dispersion of analyst forecasts, in the order. See section 3 for details. The heteroskedasticity robust t statistics, in italics, are obtained by regressing individual stock returns on a set of ten dummy variables, one for each quintile-news pair, allowing for clustering within periods. We dropped stocks whose immediate abnormal return was inconsistent with the news, i.e. stocks with positive immediate (negative) returns for the formation of the bad (good) news portfolios.

Panel A: Abnormal returns in the month following the negative or positive analyst forecast revision

	Sorted by 1/MV				*Sorted by 1/COV*				*Sorted by 1/AGE*			
Uncertainty	Bad news	Good news	Good - bad		Bad news	Good news	Good - bad		Bad news	Good news	Good - bad	
Q1 (low)	**-0.00**	**0.36**	**0.36**	*1.4*	**0.16**	**0.56**	**0.40**	*1.3*	**0.03**	**0.56**	**0.53**	*2.3*
Q2	**0.12**	**0.45**	**0.33**	*1.1*	**-0.13**	**0.49**	**0.62**	*2.0*	**0.13**	**0.92**	**0.79**	*3.0*
Q3	**-0.03**	**0.68**	**0.71**	*2.2*	**-0.09**	**0.75**	**0.84**	*2.9*	**-0.15**	**1.09**	**1.24**	*3.9*
Q4	**-0.25**	**1.34**	**1.59**	*5.5*	**-0.15**	**1.26**	**1.42**	*5.3*	**-0.10**	**1.12**	**1.22**	*3.9*
Q5 (high)	**-0.47**	**1.96**	**2.43**	*9.4*	**-0.40**	**1.89**	**2.29**	*8.2*	**-0.55**	**1.14**	**1.68**	*5.4*
Q5-Q1	**-0.47**	**1.60**			**-0.56**	**1.33**			**-0.58**	**0.57**		
	-1.6	*5.1*			*-2.2*	*4.5*			*-1.5*	*1.7*		
	Sorted by SIGMA				*Sorted by CVOL*				*Sorted by DISP*			
	Bad news	Good news	Good - bad		Bad news	Good news	Good - bad		Bad news	Good news	Good - bad	
Q1 (low)	**0.23**	**0.48**	**0.25**	*1.4*	**0.27**	**0.61**	**0.34**	*1.5*	**0.08**	**0.66**	**0.59**	*1.9*
Q2	**0.13**	**0.66**	**0.53**	*2.3*	**-0.13**	**0.68**	**0.80**	*3.3*	**0.12**	**0.55**	**0.43**	*1.5*
Q3	**-0.20**	**0.95**	**1.15**	*3.8*	**0.01**	**0.86**	**0.86**	*2.9*	**-0.02**	**0.57**	**0.59**	*2.1*
Q4	**-0.33**	**1.26**	**1.59**	*4.4*	**0.06**	**0.92**	**0.85**	*2.5*	**-0.16**	**1.00**	**1.16**	*4.0*
Q5 (high)	**-0.44**	**1.44**	**1.88**	*4.7*	**0.09**	**1.62**	**1.53**	*3.8*	**-0.50**	**1.41**	**1.91**	*5.3*
Q5-Q1	**-0.67**	**0.96**			**-0.18**	**1.01**			**-0.57**	**0.75**		
	-1.1	*1.7*			*-0.4*	*2.2*			*-2.0*	*2.6*		

Panel B: Abnormal returns in the month of the negative or positive analyst forecast revision

	Sorted by 1/MV				*Sorted by 1/COV*				*Sorted by 1/AGE*			
Uncertainty	Bad news	Good news	Good - bad		Bad news	Good news	Good - bad		Bad news	Good news	Good - bad	
Q1 (low)	**-6.57**	**7.34**	**13.90**	*35.1*	**-8.12**	**8.41**	**16.54**	*42.8*	**-6.96**	**7.50**	**14.46**	*45.2*
Q2	**-8.15**	**9.15**	**17.30**	*41.4*	**-9.00**	**9.67**	**18.67**	*42.9*	**-8.28**	**9.41**	**17.69**	*44.4*
Q3	**-9.71**	**10.87**	**20.58**	*46.4*	**-9.94**	**10.68**	**20.62**	*46.6*	**-9.84**	**10.86**	**20.70**	*51.2*
Q4	**-11.31**	**12.38**	**23.69**	*55.4*	**-10.71**	**11.84**	**22.55**	*51.0*	**-11.11**	**12.47**	**23.58**	*50.2*
Q5 (high)	**-12.46**	**13.38**	**25.84**	*64.5*	**-10.57**	**12.82**	**23.39**	*60.3*	**-12.26**	**13.19**	**25.45**	*52.9*
Q5-Q1	**-5.89**	**6.04**			**-2.45**	**4.41**			**-5.30**	**5.69**		
	-41.0	*23.4*			*-16.4*	*19.3*			*-28.8*	*23.0*		
	Sorted by SIGMA				*Sorted by CVOL*				*Sorted by DISP*			
	Bad news	Good news	Good - bad		Bad news	Good news	Good - bad		Bad news	Good news	Good - bad	
Q1 (low)	**-5.03**	**5.47**	**10.50**	*41.1*	**-6.38**	**6.61**	**13.00**	*41.0*	**-8.63**	**9.21**	**17.84**	*41.8*
Q2	**-7.01**	**7.37**	**14.38**	*47.2*	**-7.94**	**8.33**	**16.27**	*45.6*	**-8.67**	**9.30**	**17.97**	*44.2*
Q3	**-8.96**	**9.77**	**18.73**	*49.1*	**-8.97**	**9.75**	**18.73**	*49.3*	**-9.38**	**10.25**	**19.63**	*46.6*
Q4	**-11.53**	**12.47**	**24.00**	*51.5*	**-9.90**	**11.47**	**21.37**	*52.2*	**-10.07**	**10.58**	**20.65**	*50.1*
Q5 (high)	**-15.63**	**18.07**	**33.70**	*52.0*	**-11.61**	**13.91**	**25.52**	*56.4*	**-11.53**	**12.89**	**24.43**	*46.6*
Q5-Q1	**-10.60**	**12.60**			**-5.22**	**7.30**			**-2.90**	**3.68**		
	-42.2	*27.7*			*-31.3*	*23.3*			*-19.1*	*14.3*		

The results are broadly confirmed by the other proxies.[15] Overall, this evidence is coherent with Zhang (2006): the higher the uncertainty, the stronger the price continuation, in either direction.

Panel B of table 2 reports the stock returns in the month of the analyst earning forecast revision, to focus on the immediate effect of the revision. If higher uncertainty leads to news being incorporated more slowly into stock prices, one would expect the immediate price reaction to be large for low uncertainty stocks, and small for high uncertainty ones. The table reveals quite a different story: as in panel A, the price reaction increases with uncertainty. According to 1/*MV*, the yield difference between good and bad news stocks is 13.9 percentage points for low uncertainty stocks, and 25.8 points for high uncertainty ones. These very large figures are due to our choice to eliminate observations whose immediate return is inconsistent with the news, discussed above.

This result suggests that the immediate reaction of low uncertainty stocks to news is relatively low, or that the news "hitting" these stocks are relatively "small". To gather evidence about these two hypotheses, in figure 2 we plot the shocks S_T^j, together with the immediate returns from table 2, against uncertainty (for parsimony, we take averages over the six uncertainty proxies). The figure clearly shows that the absolute magnitude of the shocks is increasing in the level of information uncertainty. The relatively high price continuation for the stocks of high uncertainty firms, also documented in previous literature, may be exclusively due to the fact that these stocks are subject to larger shocks. This finding is quite intuitive, as some of the uncertainty proxies, e.g. *SIGMA* (the standard deviation of weekly stock returns) should be clearly proportional to the "size" of the news.

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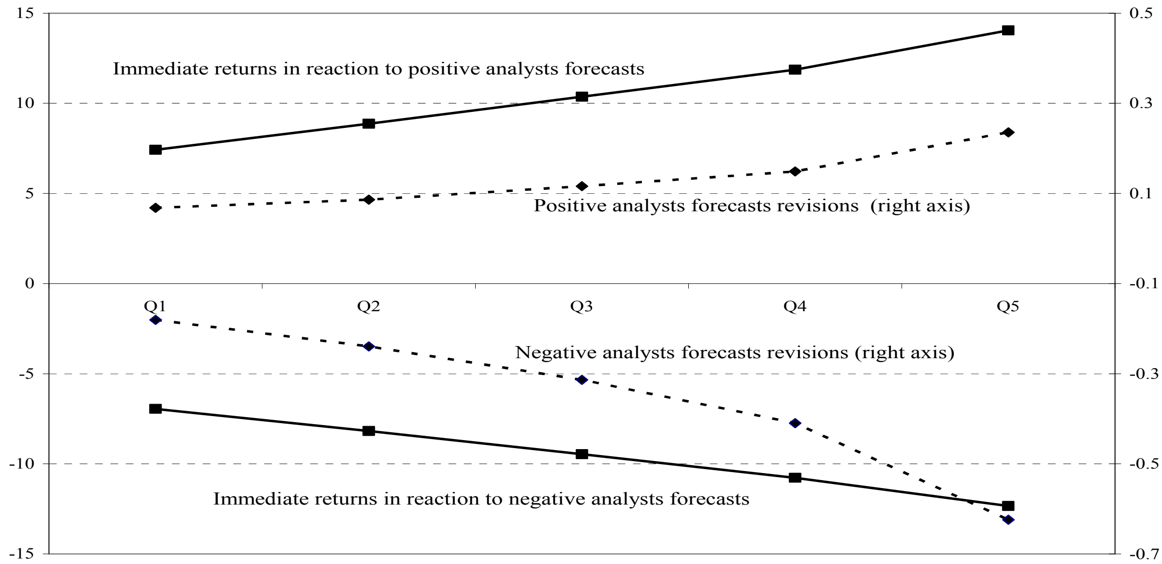
15 Similar patterns are obtained if table 2 is replicated with the full dataset, i.e. without dropping the observations whose immediate reaction is inconsistent with the news (see table A.1 in the appendix). In this case the returns from the good minus bad strategy are positive and significant for all uncertainty quintiles. The tables were also replicated with absolute returns, with qualitatively unchanged results (not reported).

Fig. 2 - Immediate abnormal stock returns and analyst forecasts revisions of quarterly earnings vs. information uncertainty

(percentage values)

The horizontal axis measures uncertainty quintiles, from low (Q1) to high (Q5). The curves of immediate returns are obtained as averages of the percentage abnormal returns reported in table 2, equally weighted across the six uncertainty proxies. The curves for analyst forecasts revisions are obtained in a similar fashion. The revisions are computed as the average forecast for the current month minus that of the past month, normalized by the stock's lagged price (see section 3 for details).



4.2 *Assessing stock price sluggishness*

Estimates of our measures of stock price sluggishness (1) through (4) are reported in panels A through D of table 3, in the order. For reasons which we shall discuss in the next subsection, let us begin by considering panel B, reporting the share of stocks displaying price continuation in the month following the release of the news. As argued in section 2, if the adjustment to the news is immediate the stock price should adjust downwards (upwards) following bad (good) news, but in the next period the likelihood of an upward movement should be the same as that of a downward movement, i.e. 50 percent. By contrast, in the presence of underreaction the share of observations displaying price continuation should be larger than 50 percent.

Table 3 - Stock price sluggishness and information uncertainty
News: analyst forecast revisions

(percentage values; t statistics in italics)

Bad and good news portfolios are constructed based on the revision of the monthly average analyst forecast. The Qs denote uncertainty quintiles, computed from independent sortings of the six proxies reported in the table (see section 3 and the note to table 2 for their definition and construction methodology). The ρ^U measure the ratio between delayed and immediate stock returns; ρ^U=0 corresponds to immediate price adjustment, positive values to sluggish adjustment, negative values to price reversal. The estimates in panel A are computed as the ratio between the delayed and the immediate returns from table 2. Heteroskedasticity robust t statistics are obtained via a weighted regression of single stock ratios on four portfolio dummies (high vs. low uncertainty, good vs. bad news), allowing for clustering at the date level. The weighting ensures that the regression coefficients equal the ρ^U. The shares in panel B are computed as a mean of monthly shares in each of the four portfolios. Quarterly shares are computed as the number of stocks whose return in *T*+1 has the same sign as in *T*, divided by the total number of stocks in the portfolio. Heteroskedasticity robust t statistics test the null hypothesis that the shares differ from 50, or across the four portfolios. They are derived from a time series regression of the monthly shares on four portfolio dummies. The ratio of medians is computed as the average of monthly ratios of medians, via a similar regression. The t statistics are robust to heteroskedasticity. The median of ratios is obtained via a quintile regression of single stock ratios on four portfolio dummies. We dropped stocks whose immediate abnormal return was inconsistent with the news, i.e. stocks with positive immediate (negative) returns for the formation of the bad (good) news portfolios.

Panel A: ρ^U estimated as ratio between delayed and immediate mean abnormal returns

	Sorted by 1/MV			*Sorted by 1/COV*			*Sorted by 1/AGE*		
Uncertainty	Bad news	Good news	Good - bad	Bad news	Good news	Good - bad	Bad news	Good news	Good - bad
Q1 (low)	**0.05**	**4.89**	**4.84**	**-1.93**	**6.68**	**8.61**	**-0.46**	**7.49**	**7.95**
	0.0	*2.3*	*1.8*	*-0.7*	*3.2*	*2.4*	*-0.1*	*3.1*	*1.7*
Q5 (high)	**3.81**	**14.66**	**10.85**	**3.81**	**14.76**	**10.95**	**4.47**	**8.61**	**4.14**
	1.5	*6.9*	*2.6*	*1.4*	*7.0*	*2.7*	*1.5*	*4.0*	*0.9*
Q5-Q1	**3.76**	**9.77**		**5.75**	**8.09**		**4.93**	**1.12**	
	1.4	*3.4*		*2.1*	*3.0*		*1.3*	*0.4*	
	Sorted by SIGMA			*Sorted by CVOL*			*Sorted by DISP*		
	Bad news	Good news	Good - bad	Bad news	Good news	Good - bad	Bad news	Good news	Good - bad
Q1 (low)	**-4.56**	**8.77**	**13.33**	**-4.21**	**9.24**	**13.45**	**-0.87**	**7.18**	**8.06**
	-1.1	*2.3*	*1.8*	*-1.2*	*2.8*	*2.3*	*-0.3*	*3.3*	*2.1*
Q5 (high)	**2.81**	**7.99**	**5.18**	**-0.77**	**11.62**	**12.39**	**4.29**	**10.94**	**6.65**
	0.8	*3.3*	*1.0*	*-0.2*	*4.5*	*2.4*	*1.5*	*4.7*	*1.5*
Q5-Q1	**7.37**	**-0.78**		**3.44**	**2.38**		**5.17**	**3.76**	
	1.2	*-0.1*		*0.7*	*0.5*		*1.9*	*1.5*	

Panel B: Share of stocks displaying price continuation

	Sorted by 1/MV			*Sorted by 1/COV*			*Sorted by 1/AGE*		
Uncertainty	Bad news	Good news	Good - bad	Bad news	Good news	Good - bad	Bad news	Good news	Good - bad
Q1 (low)	**50.46**	**50.67**	**0.21**	**50.12**	**50.83**	**0.70**	**50.99**	**51.02**	**0.03**
	0.6	*0.8*	*0.2*	*0.2*	*1.1*	*0.5*	*1.2*	*1.2*	*0.0*
Q5 (high)	**54.42**	**50.72**	**-3.69**	**53.60**	**50.28**	**-3.32**	**53.28**	**49.58**	**-3.70**
	5.3	*0.8*	*-3.1*	*4.3*	*0.3*	*-2.9*	*4.1*	*-0.5*	*-3.2*
Q5-Q1	**3.96**	**0.06**		**3.48**	**-0.55**		**2.29**	**-1.44**	
	3.6	*0.0*		*3.1*	*-0.4*		*2.0*	*-1.2*	
	Sorted by SIGMA			*Sorted by CVOL*			*Sorted by DISP*		
	Bad news	Good news	Good - bad	Bad news	Good news	Good - bad	Bad news	Good news	Good - bad
Q1 (low)	**49.84**	**51.38**	**1.54**	**48.67**	**51.76**	**3.08**	**50.01**	**51.05**	**1.04**
	-0.2	*1.3*	*1.1*	*-1.4*	*1.5*	*2.1*	*0.0*	*1.3*	*0.8*
Q5 (high)	**54.50**	**49.06**	**-5.44**	**53.47**	**51.40**	**-2.07**	**53.15**	**49.92**	**-3.23**
	4.4	*-0.9*	*-3.7*	*3.6*	*1.3*	*-1.4*	*3.4*	*-0.1*	*-2.6*
Q5-Q1	**4.66**	**-2.32**		**4.80**	**-0.36**		**3.14**	**-1.13**	
	3.4	*-1.6*		*3.5*	*-0.2*		*2.7*	*-0.9*	

(Table 3 contd.)

Panel C: ρ^U estimated as ratio between delayed and immediate median abnormal returns

	Sorted by 1/MV			*Sorted by 1/COV*			*Sorted by 1/AGE*		
Uncertainty	Bad news	Good news	Good - bad	Bad news	Good news	Good - bad	Bad news	Good news	Good - bad
Q1 (low)	**2.65**	**3.80**	**1.15**	**1.94**	**4.76**	**2.82**	**5.20**	**3.58**	**-1.62**
	1.1	*1.2*	*0.3*	*0.7*	*1.8*	*0.7*	*1.8*	*1.2*	*-0.4*
Q5 (high)	**12.93**	**-0.40**	**-13.33**	**12.92**	**2.44**	**-10.48**	**10.55**	**1.17**	**-9.39**
	4.5	*-0.1*	*-3.0*	*4.4*	*0.7*	*-2.3*	*3.4*	*0.4*	*-2.2*
Q5-Q1	**10.28**	**-4.20**		**10.97**	**-2.33**		**5.35**	**-2.41**	
	2.7	*-0.9*		*2.7*	*-0.5*		*1.3*	*-0.6*	
	Sorted by SIGMA			*Sorted by CVOL*			*Sorted by DISP*		
	Bad news	Good news	Good - bad	Bad news	Good news	Good - bad	Bad news	Good news	Good - bad
Q1 (low)	**-0.03**	**5.67**	**5.70**	**-3.46**	**2.58**	**6.04**	**0.46**	**3.72**	**3.26**
	0.0	*1.2*	*1.0*	*-1.0*	*0.5*	*1.0*	*0.2*	*1.1*	*0.8*
Q5 (high)	**12.30**	**-1.66**	**-13.96**	**10.31**	**3.32**	**-6.99**	**10.29**	**1.49**	**-8.81**
	3.8	*-0.6*	*-3.2*	*2.6*	*0.9*	*-1.3*	*2.9*	*0.5*	*-1.8*
Q5-Q1	**12.33**	**-7.33**		**13.77**	**0.74**		**9.83**	**-2.24**	
	2.6	*-1.3*		*2.6*	*0.1*		*2.2*	*-0.5*	

Panel D: ρ^U estimated as median of ratios between delayed and immediate abnormal returns

	Sorted by 1/MV			*Sorted by 1/COV*			*Sorted by 1/AGE*		
Uncertainty	Bad news	Good news	Good - bad	Bad news	Good news	Good - bad	Bad news	Good news	Good - bad
Q1 (low)	**1.98**	**2.86**	**0.88**	**0.63**	**3.21**	**2.58**	**3.25**	**2.92**	**-0.33**
	1.9	*1.1*	*0.5*	*0.6*	*1.2*	*1.5*	*3.2*	*1.1*	*-0.2*
Q5 (high)	**11.36**	**6.01**	**-5.34**	**9.98**	**7.14**	**-2.84**	**9.06**	**2.63**	**-6.43**
	8.5	*2.3*	*-3.2*	*6.6*	*2.5*	*-1.5*	*6.5*	*1.0*	*-3.7*
Q5-Q1	**9.38**	**3.16**		**9.34**	**3.93**		**5.81**	**-0.28**	
	6.5	*1.7*		*5.9*	*1.9*		*3.9*	*-0.1*	
	Sorted by SIGMA			*Sorted by CVOL*			*Sorted by DISP*		
	Bad news	Good news	Good - bad	Bad news	Good news	Good - bad	Bad news	Good news	Good - bad
Q1 (low)	**-0.19**	**4.76**	**4.95**	**-2.82**	**6.89**	**9.71**	**2.03**	**2.86**	**0.83**
	-0.2	*1.8*	*3.0*	*-2.4*	*2.3*	*5.1*	*2.0*	*1.1*	*0.5*
Q5 (high)	**11.22**	**0.96**	**-10.25**	**8.86**	**3.78**	**-5.08**	**10.27**	**3.14**	**-7.14**
	8.6	*0.4*	*-6.2*	*5.9*	*1.2*	*-2.7*	*7.9*	*1.2*	*-4.4*
Q5-Q1	**11.40**	**-3.80**		**11.68**	**-3.11**		**8.24**	**0.27**	
	8.1	*-2.1*		*7.0*	*-1.5*		*5.8*	*0.2*	

Consider first the bad news groups. The shares for the low uncertainty stocks are slightly lower or higher than 50, depending on the proxy considered, but never statistically different from this value. By contrast, for the high uncertainty groups the percentage is significantly larger than 50 for all proxies considered. Furthermore, the difference between the high and low uncertainty shares is consistently positive and statistically significant, as can be seen from the difference reported in the rows labeled “Q5-Q1”. Therefore, for the bad news stocks there is evidence that the adjustment speed is higher among high uncertainty stocks.

For the good news groups the table reveals rather different patterns. The percentage of stocks whose price displays continuation is never statistically different from 50 for either the low and high uncertainty stocks. The difference high-minus-low is negative in five out of six cases, and it is never significant, suggesting that in the case of good news the adjustment speed is equal across low and high uncertainty stocks. The evidence in panel B is closely matched by the two estimators of ρ in panels C and D (the ratio of the median values of r_{T+1}^{j} and r_{T}^{j}, the median value of the ratios computed at the individual stock level).

Summing up, the median-based estimators (2) through (4) strongly suggest that high uncertainty stocks display relatively more sluggish price adjustment than low uncertainty ones in reaction to bad news, whereas the adjustment speed is similar in the case of good news.

4.3 Median- vs. mean-based estimators

Consider now the mean-based estimator of ρ, in panel A of table 3 (recall that these estimates are equal by construction to the ratio between delayed and immediate mean returns from table 2). For the bad news group, the estimated ρ^H are positive for all 6 proxies, whereas the ρ^L are zero or negative; however, none of them are statistically different from zero. The null hypothesis $\rho^H = \rho^L$ is rejected in favor of the alternative $\rho^H > \rho^L$ by one out of six uncertainty proxies (1/*COV*). For the good news group, both ρ^H and ρ^L are significantly greater than zero for all six proxies. In this case, the null hypothesis $\rho^H = \rho^L$ is rejected by 1/*MV* and 1/*COV*.

This evidence differs rather sharply from that emerging from the previous sub-section. As discussed in section 2, this apparent contrast is due to the asymmetric distribution of r_{T+d}^{j}.

Consider e.g. the high uncertainty, bad news portfolio for *CVOL*. The estimated ratio of means (-0.8), together with the estimated share (53.5), suggest that the distribution is skewed to the right: more than 50 percent of the stocks record relatively modest price continuation, whereas a relatively small fraction displays relatively strong reversal. This raises the question of what is the right measure of adjustment speed. To the extent that, when discussing high vs. low uncertainty stocks, one has in mind a "representative" stock for each category, we believe that the median-based estimators should be preferred, as they are less influenced by extreme observations.

This difference between mean- and median-based estimators of adjustment speed is important because most empirical work on stock price continuation patterns focuses on mean returns. Our evidence suggests that, depending on the purpose of the analysis, alternative estimators could be preferred.

4.4 Four-factor model results

In this subsection we adopt the factor model approach proposed by Fama and French (1996) to obtain alternative measures of immediate and delayed returns. The idea is to eliminate the portion of returns predictability that can be attributed to rational causes, e.g. risk. For each of our four portfolios of stocks (low vs. high uncertainty, bad vs. good news) we compute the average absolute return in the month of the portfolio formation and in the following month, denoted R_T^U and R_{T+1}^U, respectively. We replicate this procedure for each month in our sample, and obtain monthly time series of returns for each portfolio. We adopt the four-factor model proposed by Carhart (1997) and estimate the following regressions:

$$
\begin{aligned}
&R_T^U - r_{fT} = \gamma_I^U + \delta_{I1}^U(r_T^M - r_{fT}) + \delta_{I2}^U SMB_T + \delta_{I3}^U HML_T + \delta_{I4}^U UMD_T + \varepsilon_{IT}^U \\
(5)\quad & \\
&R_{T+1}^U - r_{fT+1} = \gamma_D^U + \delta_{D1}^U(r_{T+1}^M - r_{fT+1}) + \delta_{D2}^U SMB_{T+1} + \delta_{D3}^U HML_{T+1} + \delta_{D4}^U UMD_{T+1} + \varepsilon_{DT+1}^U \,.
\end{aligned}
$$

where the superscripts $U = H, L$ denote high and low uncertainty, as usual (superscripts $N = B$, G have been omitted); r_T^M is the market return, computed from the value-weighted CRSP index; r_{fT} is the risk-free rate; *SMB* (the size premium) and *HML* (the value premium) are the other two Fama-French factors; and *UMD* captures momentum. The coefficients γ_I^U and γ_D^U measure the immediate and the delayed reaction to the news, net of the effect captured by the factors on the right-hand side of the equations. The ρs are estimated by taking the ratio γ_D^U / γ_I^U for each portfolio (p-values are not available).

The results are in table 4. Consider the bad news portfolios first. The estimates of γ_I are all significant and negative, and the γ_I^H are roughly twice the size of the γ_I^L, in line with the evidence in table 2, panel A. The estimated γ_D for the low uncertainty portfolios are all positive, and statistically significant in three out of six cases, suggesting that the adjustment is immediate or that there is reversal. For the high uncertainty portfolios the estimated γ_D are instead negative in five out of six cases, and significant in two. The overall pattern for bad news is similar to the one in table 2, panel B. The ratios suggest that $\rho^H > \rho^L$ holds in the case of bad news.

For the positive forecast revisions, in panel B, all the γ_D^L are positive, and four out of six are significantly greater than zero. All the γ_D^H are positive and statistically significant. Based on the point estimates of the ratios, the inequality $\rho^H > \rho^L$ holds for five out of six proxies, but for three of them the ρs have a rather similar magnitude. Overall, the message emerging from table 3 seems little changed.[16]

[16] For robustness, we recomputed table 4 over the full dataset, i.e. without dropping observations whose immediate reaction is in line with the news. The evidence against the null hypothesis $\rho^H = \rho^L$ weakens further (results not reported).

Table 4 - Four factor model results
News: analyst forecast revisions

(percentage values; t statistics in italics)

The table reports the parameters γ_I^i and γ_D^i, the intercepts computed from equations (5) in the text, as well as estimates of ρ^U, computed as γ_I^i / γ_D^i. The Qs denote uncertainty quintiles, computed from independent sortings of the six proxies reported in the column headings of the table (see section 3 and the note to table 2 for their definition and construction methodology). The t statistics, in italics, are robust to heteroskedasticity.

Sorted by:	*1/MV*	*1/COV*	*1/AGE*	*SIGMA*	*CVOL*	*DISP*
Panel A: Bad news (negative forecast revisions)						
Uncertainty	*Immediate returns (γ_I^U)*					
Q1 (low)	**-6.0**	**-7.4**	**-6.4**	**-4.7**	**-6.0**	**-7.7**
	-36.9	*-38.6*	*-45.3*	*-44.4*	*-40.6*	*-37.5*
Q5 (high)	**-11.5**	**-9.8**	**-11.2**	**-14.2**	**-10.7**	**-10.3**
	57.9	*-54.7*	*-45.0*	*-44.2*	*-49.2*	*-46.5*
	Delayed returns (γ_D^U)					
Q1 (low)	**0.1**	**0.4**	**0.1**	**0.3**	**0.3**	**0.4**
	0.8	*2.4*	*0.6*	*2.6*	*1.7*	*2.0*
Q5 (high)	**-0.4**	**-0.4**	**-0.4**	**-0.3**	**0.1**	**-0.4**
	-1.7	*-1.8*	*-2.3*	*-3.3*	*0.6*	*-1.9*
	Ratio between delayed and immediate mean abnormal return (ρ^U)					
Q1 (low)	**-1.6**	**-5.0**	**-1.1**	**-6.3**	**-4.6**	**-4.7**
Q5 (high)	**3.2**	**3.6**	**3.5**	**2.1**	**-1.3**	**3.6**
Panel B: Good news (positive forecast revisions)						
Uncertainty	*Immediate returns (γ_I^U)*					
Q1 (low)	**6.9**	**7.9**	**7.0**	**5.1**	**6.1**	**8.4**
	27.6	*32.9*	*33.5*	*37.6*	*37.5*	*32.5*
Q5 (high)	**12.4**	**11.7**	**12.5**	**16.8**	**12.9**	**11.8**
	39.1	*41.2*	*35.7*	*33.8*	*37.7*	*24.7*
	Delayed returns (γ_D^U)					
Q1 (low)	**0.2**	**0.4**	**0.3**	**0.3**	**0.2**	**0.5**
	1.5	*2.3*	*2.4*	*2.5*	*1.2*	*2.9*
Q5 (high)	**1.4**	**1.1**	**0.8**	**1.1**	**1.2**	**0.8**
	6.6	*5.5*	*3.7*	*4.5*	*4.2*	*3.1*
	Ratio between delayed and immediate mean abnormal return (ρ^U)					
Q1 (low)	**3.2**	**4.8**	**4.9**	**6.5**	**3.6**	**5.8**
Q5 (high)	**11.5**	**9.5**	**6.2**	**6.3**	**9.3**	**6.5**

4.5 Robustness

The above results proved robust to a series of alternative assumptions and methodological choices, which we summarize in what follows. One obvious candidate explanation for the difference in pattern across the good and bad news portfolios is the method chosen to assign stocks to these groups, based on analyst forecasts revisions. In particular, analyst forecasts may suffer from biases (see e.g. Trueman (1994); Jackson and Johnson (2006)). Thus, we replicate the key steps of the analysis with an alternative definition of $S^{j}_{T,\tau}$. Specifically, stocks were assigned to the good and bad news groups based on whether their immediate return r^{j}_{T} exceeded 0.5 percent or was below -0.5 percent in the month with a non-zero average forecasts revision. In so doing, we use all observations, i.e. we do not discard observations whose immediate reaction is inconsistent with the sign of the news, as we do to obtain our baseline results. This definition of news is analogous to the one we adopt in section 5. The results are in table A.2 in the appendix. The patterns on stock price sluggishness documented in the previous subsection come out strengthened. Specifically, our median-based estimators now strongly suggest that price adjustment of high uncertainty stocks is relatively slow following bad news, but relatively fast following good news.[17]

Several other checks confirmed the results of the previous sub-sections (results not reported). First, our measure of immediate returns, r^{j}_{T}, may be biased as it may incorporate a delayed effect of last month's analyst forecast revision, S^{j}_{T-1}; similarly, r^{j}_{T+1} may also incorporate the immediate effect of S^{j}_{t+1}. This problem may be particularly relevant if there is significant autocorrelation in S^{j}_{T}. To make sure that our results are not driven by this effect we restrict the analysis to those stocks for which the conditions $S^{j}_{T-1} = 0$, $S^{j}_{T} \neq 0$ and $S^{j}_{t+1} = 0$ hold. Second, we tried to control for the quarterly release of earnings data. Once in each

[17] Results were also replicated using a zero threshold for immediate returns (instead of the plus/minus 0.5 percent threshold) to define the bad or good news groups. This robustness check controls for the following potential source of bias. Suppose that the immediate return is given by the genuine reaction to the surprise plus a zero mean random noise. Then stocks with relatively low price adjustment speed, i.e. with relatively small immediate reaction, would be more likely do be dropped under our baseline methodology.

quarter, monthly returns are affected not only by S_T^j, but also by the actual release of earnings data. This may have an important effect on returns, independent of the effect of S_T^j. As a crude but straightforward way to control for this effect, we restricted the sample to the months not affected by the release of the quarterly earnings. Third, our results were replicated over the two sub-samples 1985-1995 and 1996-2005. Fourth, in the light of evidence suggesting that the delayed effect of news can last for several months (e.g. Zhang (2006)), we experimented with different definitions of delayed returns. Specifically, we redefined r_{t+d}^j as the return in the two, three, six and twelve months following the release. Fifth, we pooled stocks in the first and second uncertainty quintiles, and analyzed their behavior vis-à-vis stocks in the fourth and fifth uncertainty quintiles. Finally, one could argue that small absolute values of S_T^j incorporate an excessive amount of noise, and could therefore reduce the precision of the estimates. Thus, we attributed observations with small absolute values of S_T^j to the $S_T^j = 0$ group. We experimented with various definitions of "small", so as to significantly reduce the number of observations in the good and bad news groups.

5. Uncertainty and the post-earnings announcement drift

A large literature, at which we briefly hinted in the introduction, has documented the post-earnings announcement drift (PEAD), the fact that stock prices continue to drift in the direction of the earnings surprise in the days or weeks following the earnings release. The anomaly is often attributed to investors' slow response to new information.

Therefore, in this section we look at stock prices adjustment speed using data on stock returns around and after the announcement of quarterly earnings. This second set of exercises allows us to overcome several difficulties that in principle could mar the evidence discussed thus far. In essence, the arrival of the news, and therefore the immediate and the delayed stock price reaction to them, should now be measured with higher precision.

Stocks in each cross-section are first separated into good and bad news groups; each group is then sorted in increasing order of uncertainty, based on our usual proxies. The analysis is then conducted on the bad vs. good news, low vs. high uncertainty portfolios. While the analysis is similar to that of the previous section, the following differences are worth highlighting.

First, focusing on actual earnings releases yields four observations for each year and firm. Now subscripts measure days, and T denotes the day of the actual earnings release; the immediate and delayed cumulative abnormal returns are denoted by $r^j_{T-1,T+1}$ and $r^j_{T+2,T+d}$, respectively. Our baseline results are derived using d=30 calendar days (alternative choices are discussed in section 5.3, devoted to the robustness checks).

Second, our baseline proxy for news is now based on positive and negative excess returns on the day of the earnings release (see e.g. Frazzini (2006); in the notation of section 2, we set $S^j_T = r^j_{T-1,T+1}$). Specifically, the good (bad) news portfolios comprise stocks whose $r^j_{T-1,T+1}$ exceeds 0.5 percent (is below -0.5 percent). This allows us to completely disregard analyst forecasts, avoiding the potential problems discussed in section 4.4. However, we also replicate the analysis with an alternative definition of news, i.e. earnings surprises, computed as actual announcements of quarterly earnings minus the average of analyst forecasts recorded in the previous month. The related results are discussed in section 5.3.

Third, abnormal returns are computed using the market model, which is widely used in the event studies literature (in section 5.3 we also use returns in deviation from the market, as in section 4). We proceed as follows. For each stock and earnings announcement date T, we estimate the following regression over the 60 calendar days period before each announcement:

$$R_s^j = \delta_0^j + \delta_1^j r_s^M + \varepsilon_s^j, \qquad s = T\text{-}60,\ T\text{-}59,\ \ldots.\ T\text{-}2, \tag{6}$$

where R_s^j denotes the absolute return of stock *j* and r_s^M is the market return, computed using the value-weighted index.[18] Immediate and delayed abnormal returns are then defined as $r_{T-1,T+1}^j = \prod_{l=-1}^{1}(1+\hat{\varepsilon}_{T+l}^j)$ and $r_{T+2,T+d}^j = \prod_{l=2}^{d}(1+\hat{\varepsilon}_{T+l}^j)$, where hats denote the residuals obtained from equation (6).

We deviate from the typical PEAD analysis in several respects. First, in this literature, news are generally computed as standardized unexpected earnings (current minus past quarter earnings, normalized by the standard deviation of earnings). Furthermore, abnormal returns are often computed as in section 4 (i.e. in deviation from the market return) or with matched portfolios (e.g. by size, book-to-market value; see Bernard and Thomas (1989, 1990), Hou and Moskowitz (2005)). Since we want a genuine measure of the (immediate and delayed) stock price reaction to the earnings surprise, we need to eliminate from the returns the part which can be predicted based on information available prior to the release. This includes a possible positive or negative drift – the coefficient δ_0^j in equation (6) – which may be present the days or weeks prior to the announcement (see Bernard and Thomas (1989)).

5.1 Behavior of immediate and delayed returns

Table 5 – the analogue of table 2 – shows average immediate and delayed abnormal returns for each proxy-quintile-news portfolio. Consider the delayed returns, in Panel A.

---

18 Additional factors could be introduced in equation (6), but there is evidence that doing so would add little explanatory power to the market model (see Campbell, Lo and MacKinlay (1997)).

Table 5 - Average abnormal stock returns and information uncertainty
News: quarterly earnings announcements

(percentage values; t statistics in italics)

Bad and good news portfolios are constructed based on the sign of the return on the day of the quarterly earnings announcement, $r^j_{T-1,T+1}$ (the immediate return). Specifically, the good (bad) news portfolios comprise stocks whose $r^j_{T-1,T+1}$ exceeds 0.5 percent (is below -0.5 percent). The Qs denote uncertainty quintiles, computed from independent sortings of the six proxies reported in the table (see section 3 and the note to table 2 for their definition and construction methodology). Abnormal returns are computed using the market model, as described in section 5. The heteroskedasticity robust t statistics, in italics, are obtained by regressing individual stock returns on a set of ten dummy variables, one for each quintile-news pair, allowing for clustering at the date level.

Panel A: Abnormal returns in the month following the 3-day window around negative or positive earnings surprises

	Sorted by 1/MV				*Sorted by 1/COV*				*Sorted by 1/AGE*			
Uncertainty	Bad news	Good news	Good - bad		Bad news	Good news	Good - bad		Bad news	Good news	Good - bad	
Q1 (low)	**-1.57**	**0.91**	**2.48**	*14.3*	**-1.01**	**1.76**	**2.77**	*14.8*	**-0.97**	**1.82**	**2.80**	*16.7*
Q2	**-2.30**	**1.05**	**3.35**	*16.3*	**-1.54**	**1.86**	**3.41**	*15.5*	**-1.80**	**1.72**	**3.52**	*16.7*
Q3	**-2.42**	**1.59**	**4.01**	*19.6*	**-1.95**	**1.75**	**3.70**	*14.5*	**-2.03**	**1.36**	**3.39**	*16.0*
Q4	**-2.28**	**1.76**	**4.04**	*13.4*	**-2.80**	**1.20**	**4.00**	*19.0*	**-2.65**	**1.47**	**4.13**	*19.0*
Q5 (high)	**-2.04**	**2.22**	**4.26**	*18.2*	**-3.59**	**0.92**	**4.52**	*15.3*	**-3.24**	**1.13**	**4.37**	*16.1*
Q5-Q1	**-0.47**	**1.31**			**-2.58**	**-0.84**			**-2.26**	**-0.69**		
	-1.1	*2.9*			*-7.6*	*-2.5*			*-5.0*	*-1.5*		
	Sorted by SIGMA				*Sorted by CVOL*				*Sorted by DISP*			
	Bad news	Good news	Good - bad		Bad news	Good news	Good - bad		Bad news	Good news	Good - bad	
Q1 (low)	**-0.67**	**1.57**	**2.25**	*14.2*	**-1.02**	**1.41**	**2.42**	*13.7*	**-2.09**	**1.35**	**3.44**	*15.8*
Q2	**-1.20**	**1.53**	**2.73**	*20.6*	**-1.42**	**1.69**	**3.11**	*16.3*	**-1.54**	**1.39**	**2.93**	*14.0*
Q3	**-1.82**	**1.68**	**3.50**	*19.4*	**-1.76**	**1.94**	**3.70**	*16.3*	**-1.77**	**1.64**	**3.41**	*13.8*
Q4	**-2.58**	**1.51**	**4.09**	*16.1*	**-1.85**	**1.76**	**3.60**	*17.4*	**-1.83**	**1.67**	**3.50**	*16.0*
Q5 (high)	**-4.19**	**1.25**	**5.44**	*15.8*	**-3.21**	**1.23**	**4.44**	*13.6*	**-2.11**	**2.06**	**4.16**	*14.1*
Q5-Q1	**-3.51**	**-0.32**			**-2.19**	**-0.18**			**-0.01**	**0.71**		
	-5.8	*-0.6*			*-4.8*	*-0.5*			*0.0*	*2.5*		

Panel B: Abnormal returns in the 3-day window around negative or positive earnings surprises

	Sorted by 1/MV				*Sorted by 1/COV*				*Sorted by 1/AGE*			
Uncertainty	Bad news	Good news	Good - bad		Bad news	Good news	Good - bad		Bad news	Good news	Good - bad	
Q1 (low)	**-4.14**	**4.28**	**8.41**	*31.6*	**-4.82**	**5.13**	**9.95**	*33.9*	**-3.84**	**4.17**	**8.01**	*38.7*
Q2	**-5.04**	**5.12**	**10.16**	*34.8*	**-5.42**	**5.52**	**10.94**	*36.6*	**-4.87**	**5.05**	**9.92**	*40.3*
Q3	**-5.74**	**5.76**	**11.49**	*39.3*	**-5.73**	**5.92**	**11.65**	*41.4*	**-5.56**	**5.77**	**11.33**	*43.2*
Q4	**-6.08**	**6.19**	**12.28**	*47.7*	**-5.65**	**5.75**	**11.40**	*51.5*	**-6.27**	**6.37**	**12.64**	*45.9*
Q5 (high)	**-6.17**	**6.61**	**12.78**	*69.7*	**-5.49**	**5.62**	**11.11**	*60.3*	**-6.74**	**6.72**	**13.46**	*45.3*
Q5-Q1	**-2.03**	**2.33**			**-0.67**	**0.49**			**-2.90**	**2.54**		
	-19.2	*23.8*			*-5.4*	*5.1*			*-29.9*	*27.1*		
	Sorted by SIGMA				*Sorted by CVOL*				*Sorted by DISP*			
	Bad news	Good news	Good - bad		Bad news	Good news	Good - bad		Bad news	Good news	Good - bad	
Q1 (low)	**-2.96**	**3.22**	**6.18**	*41.8*	**-3.39**	**3.62**	**7.01**	*43.6*	**-5.49**	**5.53**	**11.02**	*35.6*
Q2	**-4.00**	**4.29**	**8.30**	*47.9*	**-4.25**	**4.55**	**8.80**	*43.3*	**-5.24**	**5.44**	**10.69**	*39.0*
Q3	**-5.23**	**5.34**	**10.57**	*42.8*	**-5.03**	**5.36**	**10.39**	*44.0*	**-5.32**	**5.47**	**10.79**	*37.9*
Q4	**-6.63**	**6.75**	**13.38**	*43.4*	**-5.71**	**6.01**	**11.72**	*44.1*	**-5.37**	**5.67**	**11.04**	*43.1*
Q5 (high)	**-8.24**	**8.30**	**16.54**	*41.1*	**-6.92**	**7.00**	**13.92**	*48.8*	**-5.88**	**6.00**	**11.88**	*42.3*
Q5-Q1	**-5.28**	**5.08**			**-3.53**	**3.38**			**-0.38**	**0.48**		
	-32.3	*33.4*			*-28.5*	*35.5*			*-4.7*	*5.1*		

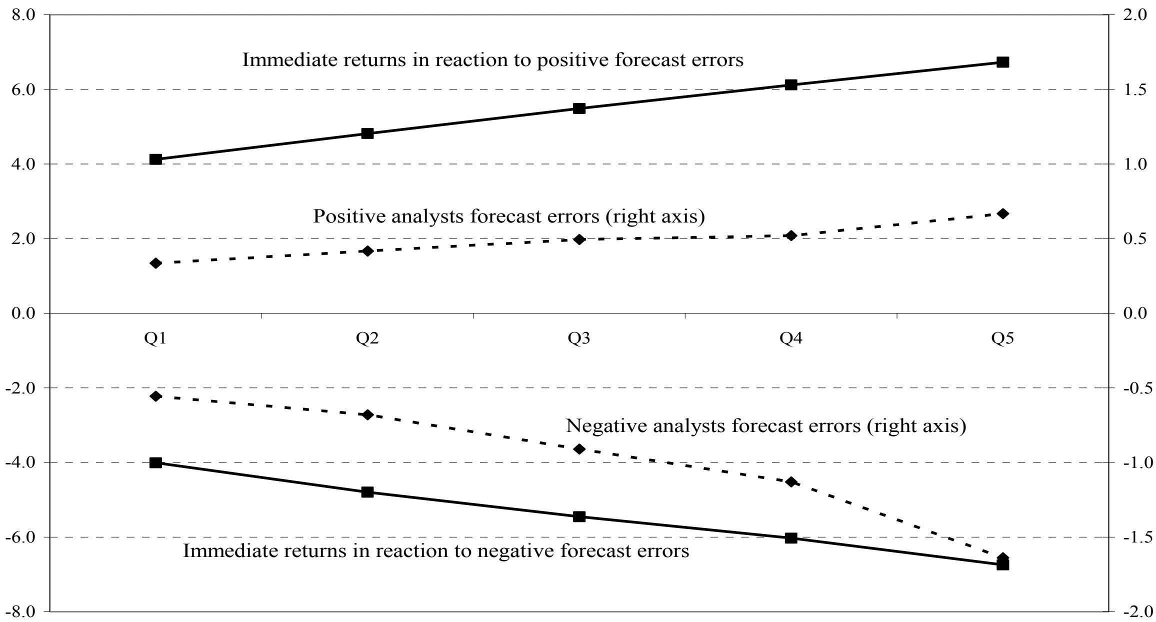
There is evidence of price continuation for both bad and good news portfolios. In the month following the release of negative earnings surprises (captured by negative immediate returns), the high-minus-low uncertainty difference is positive and significant in four out of six cases, signaling that price continuation is stronger for high uncertainty stocks; for the remaining two proxies (*1/MV* and *DISP*) the difference is not significant. Within the good news portfolios, the high-minus-low uncertainty difference is instead negative in four out of six cases (significant in one), positive and significant in two cases (1/*MV* and *DISP*).

The absolute value of the immediate returns $r^{j}_{T-1,T+1}$, in panel B, is increasing in uncertainty, confirming the pattern documented in table 2.

Fig. 3 - Immediate abnormal stock returns and analyst forecast errors of quarterly earnings vs. information uncertainty

(percentage values)

The horizontal axis measures uncertainty quintiles, from low (Q1) to high (Q5). The curves of immediate returns are obtained as averages of the percentage abnormal returns reported in table A.3 in the appendix, equally weighted across the six uncertainty proxies. The curves of analyst forecast errors are obtained in a similar fashion. Forecast errors are computed as actual announcements of quarterly earnings minus the average of analyst forecasts recorded in the previous month, normalized by the stock's lagged price (see section 3 for details).



To assess whether this pattern can be due to "larger" news we use our alternative measure of news, analyst forecast errors. Figure 3 plots these errors, together with average returns, against uncertainty: higher uncertainty is associated with larger errors, which cause a larger immediate reaction, in line with the results of the previous section.

5.2 Assessing stock prices sluggishness

Table 6 – the analogue of table 3 – reports our usual statistics. As before, we consider first the share of stocks displaying price continuation, in panel B. Among the bad news portfolios, the share is significantly larger than 50 percent for both the high and low uncertainty stocks; the difference between the former and the latter is significant and positive for four proxies, 1/*COV*, 1/*AGE, SIGMA* and *CVOL*, not significant for 1/*MV* and *DISP*. Considering the good news portfolios, the share is always statistically greater than 50 among the low uncertainty stocks, and mostly not different from 50 among the high uncertainty stocks. The difference high-minus-low uncertainty is negative in all cases and significant in four out of six.

The median-based estimators, in panels C and D, strengthen somewhat the message emerging from the shares: among the bad news groups, the estimated ρs for the high uncertainty portfolios are almost always significantly larger than for the low uncertainty ones. For the good news group, both estimators suggest that the adjustment is significantly faster for high uncertainty stocks ($\rho^H < \rho^L$) when uncertainty is proxied by 1/*COV*, 1/*AGE, SIGMA* and *CVOL* ; based on 1/*MV* and *DISP* the adjustment speed is instead the same.

Finally, the ρs estimated as a ratio of means, in panel A, broadly confirm the evidence from panels B through D, suggesting that the asymmetry of the distribution of delayed returns detected and discussed in section 4.3 is not so strong in this dataset.

Table 6 - Stock price sluggishness and information uncertainty
News: quarterly earnings announcements

(percentage values; t statistics in italics)

Bad and good news portfolios are constructed based on the sign of the return on the day of the quarterly earnings announcement (the immediate return, $r^{j}_{T-1,T+1}$). Specifically, the good (bad) news portfolios comprise stocks whose $r^{j}_{T-1,T+1}$ exceeds 0.5 percent (is below -0.5 percent). The Qs denote uncertainty quintiles, computed from independent sortings of the six proxies reported in the table (see the note to table 2 and section 3 for their definition and construction methodology). The ρ^{U} measure the ratio between delayed and immediate stock returns; ρ^{U}=0 corresponds to immediate price adjustment, positive values to sluggish adjustment, negative values to price reversal. The estimates in panel A are computed as the ratio between the delayed and the immediate returns from table 5. The related heteroskedasticity robust t statistics are obtained via a weighted regression of single stock ratios on four portfolio dummies (high vs. low uncertainty, good vs. bad news), allowing for clustering at the date level. The weighting ensures that the regression coefficients equal the ρ^{U}. The shares in panel B are computed as a mean of quarterly shares in each of the four portfolios. Quarterly shares are computed as the number of stocks whose return in T+1 has the same sign as in T, divided by the total number of stocks in the portfolio. The heteroskedasticity robust t statistics test the null hypothesis that the shares differ from 50, or across the four portfolios. They are derived from a time series regression of the quarterly shares on four portfolio dummies. The ratio of medians is computed as the average of quarterly ratios of medians, via a similar regression. The t statistics are robust to heteroskedasticity. The median of ratios is obtained via a quantile regression of single stock ratios on four portfolio dummies.

Panel A: ρ^{U} estimated as a ratio between delayed and immediate mean abnormal returns

	Sorted by 1/MV			*Sorted by 1/COV*			*Sorted by 1/AGE*		
Uncertainty	Bad news	Good news	Good - bad	Bad news	Good news	Good - bad	Bad news	Good news	Good - bad
Q1 (low)	**38.02**	**21.32**	**-16.70**	**20.97**	**34.29**	**13.32**	**25.37**	**43.74**	**18.38**
	10.3	*8.7*	*-3.3*	*5.1*	*11.1*	*2.1*	*5.2*	*10.6*	*2.2*
Q5 (high)	**33.13**	**33.59**	**0.46**	**65.44**	**16.42**	**-49.02**	**48.01**	**16.84**	**-31.17**
	4.4	*4.9*	*0.0*	*8.6*	*2.5*	*-3.7*	*6.7*	*2.4*	*-2.2*
Q5-Q1	**-4.90**	**12.27**		**44.46**	**-17.87**		**22.65**	**-26.90**	
	-0.7	*1.8*		*7.2*	*-2.9*		*3.3*	*-3.6*	
	Sorted by SIGMA			*Sorted by CVOL*			*Sorted by DISP*		
	Bad news	Good news	Good - bad	Bad news	Good news	Good - bad	Bad news	Good news	Good - bad
Q1 (low)	**22.72**	**48.83**	**26.11**	**29.98**	**38.88**	**8.90**	**38.10**	**24.39**	**-13.71**
	4.3	*10.7*	*3.0*	*5.1*	*7.0*	*0.9*	*7.3*	*5.1*	*-1.5*
Q5 (high)	**50.80**	**15.10**	**-35.70**	**46.36**	**17.61**	**-28.75**	**35.83**	**34.26**	**-1.56**
	7.0	*2.3*	*-2.7*	*7.2*	*3.4*	*-2.7*	*5.0*	*5.3*	*-0.1*
Q5-Q1	**28.08**	**-33.73**		**16.38**	**-21.27**		**-2.28**	**9.87**	
	3.5	*-4.5*		*2.2*	*-3.3*		*-0.4*	*2.1*	

Panel B: Share of stocks displaying price continuation

	Sorted by 1/MV			*Sorted by 1/COV*			*Sorted by 1/AGE*		
Uncertainty	Bad news	Good news	Good - bad	Bad news	Good news	Good - bad	Bad news	Good news	Good - bad
Q1 (low)	**58.41**	**53.47**	**-4.94**	**56.00**	**54.35**	**-1.65**	**56.37**	**55.30**	**-1.07**
	14.2	*4.3*	*-4.9*	*9.8*	*6.4*	*-1.8*	*8.7*	*7.8*	*-1.1*
Q5 (high)	**58.21**	**52.56**	**-5.66**	**62.50**	**50.39**	**-12.10**	**60.63**	**50.36**	**-10.27**
	9.1	*2.5*	*-4.2*	*14.1*	*0.4*	*-9.1*	*11.0*	*0.4*	*-7.5*
Q5-Q1	**-0.20**	**-0.92**		**6.50**	**-3.95**		**4.27**	**-4.94**	
	-0.2	*-0.7*		*6.0*	*-3.3*		*3.5*	*-4.2*	
	Sorted by SIGMA			*Sorted by CVOL*			*Sorted by DISP*		
	Bad news	Good news	Good - bad	Bad news	Good news	Good - bad	Bad news	Good news	Good - bad
Q1 (low)	**55.72**	**56.27**	**0.55**	**56.74**	**54.92**	**-1.82**	**58.62**	**52.94**	**-5.67**
	6.3	*7.9*	*0.5*	*7.1*	*4.5*	*-1.2*	*12.3*	*3.6*	*-5.3*
Q5 (high)	**61.78**	**48.84**	**-12.94**	**60.32**	**50.58**	**-9.74**	**58.44**	**52.71**	**-5.74**
	13.1	*-1.3*	*-10.1*	*9.9*	*0.6*	*-6.6*	*9.3*	*3.0*	*-4.5*
Q5-Q1	**6.06**	**-7.43**		**3.58**	**-4.34**		**-0.18**	**-0.24**	
	4.7	*-6.2*		*2.5*	*-2.8*		*-0.2*	*-0.2*	

(Table 6 contd.)

Panel C: ρ^U estimated as ratio between delayed and immediate median abnormal returns

	Sorted by 1/MV			*Sorted by 1/COV*			*Sorted by 1/AGE*		
Uncertainty	Bad news	Good news	Good - bad	Bad news	Good news	Good - bad	Bad news	Good news	Good - bad
Q1 (low)	**61.72**	**19.58**	**-42.13**	**44.81**	**26.93**	**-17.88**	**50.88**	**35.84**	**-15.04**
	14.0	*4.7*	*-7.0*	*9.4*	*6.3*	*-2.8*	*8.5*	*7.0*	*-1.9*
Q5 (high)	**62.51**	**16.78**	**-45.73**	**95.97**	**3.98**	**-91.98**	**76.63**	**0.58**	**-76.05**
	8.8	*2.0*	*-4.2*	*13.3*	*0.5*	*-8.4*	*10.5*	*0.1*	*-7.6*
Q5-Q1	**0.79**	**-2.80**		**51.16**	**-22.94**		**25.75**	**-35.26**	
	0.1	*-0.3*		*5.9*	*-2.5*		*2.7*	*-4.1*	
	Sorted by SIGMA			*Sorted by CVOL*			*Sorted by DISP*		
	Bad news	Good news	Good - bad	Bad news	Good news	Good - bad	Bad news	Good news	Good - bad
Q1 (low)	**43.09**	**42.98**	**-0.11**	**55.43**	**35.97**	**-19.45**	**62.11**	**16.63**	**-45.48**
	6.8	*7.4*	*0.0*	*6.7*	*4.1*	*-1.6*	*11.7*	*2.9*	*-5.9*
Q5 (high)	**89.62**	**-13.08**	**-102.70**	**74.21**	**-2.14**	**-76.35**	**66.42**	**20.38**	**-46.04**
	12.3	*-1.9*	*-10.2*	*9.6*	*-0.3*	*-7.5*	*8.7*	*2.8*	*-4.4*
Q5-Q1	**46.53**	**-56.07**		**18.78**	**-38.11**		**4.31**	**3.75**	
	4.8	*-6.2*		*1.7*	*-3.5*		*0.5*	*0.4*	

Panel D: ρ^U estimated as median of ratios between delayed and immediate abnormal returns

	Sorted by 1/MV			*Sorted by 1/COV*			*Sorted by 1/AGE*		
Uncertainty	Bad news	Good news	Good - bad	Bad news	Good news	Good - bad	Bad news	Good news	Good - bad
Q1 (low)	**48.89**	**16.70**	**-32.20**	**35.46**	**20.51**	**-14.95**	**41.10**	**31.04**	**-10.06**
	23.8	*3.3*	*-11.1*	*17.2*	*3.9*	*-5.1*	*19.4*	*5.9*	*-3.4*
Q5 (high)	**57.86**	**14.66**	**-43.19**	**80.78**	**2.50**	**-78.28**	**71.39**	**1.59**	**-69.80**
	28.0	*2.9*	*-14.8*	*32.2*	*0.5*	*-21.8*	*32.3*	*0.3*	*-22.4*
Q5-Q1	**8.97**	**-2.03**		**45.33**	**-18.01**		**30.29**	**-29.45**	
	3.1	*-0.7*		*13.8*	*-5.5*		*9.9*	*-9.6*	
	Sorted by SIGMA			*Sorted by CVOL*			*Sorted by DISP*		
	Bad news	Good news	Good - bad	Bad news	Good news	Good - bad	Bad news	Good news	Good - bad
Q1 (low)	**35.23**	**34.83**	**-0.39**	**41.16**	**28.85**	**-12.31**	**51.53**	**14.44**	**-37.10**
	16.8	*6.8*	*-0.1*	*13.9*	*4.0*	*-3.0*	*21.0*	*2.4*	*-10.7*
Q5 (high)	**78.01**	**-9.26**	**-87.27**	**64.63**	**-1.67**	**-66.29**	**59.16**	**15.53**	**-43.63**
	36.9	*-1.8*	*-29.3*	*21.9*	*-0.2*	*-15.9*	*24.2*	*2.6*	*-12.6*
Q5-Q1	**42.79**	**-44.09**		**23.47**	**-30.51**		**7.63**	**1.09**	
	14.4	*-14.8*		*5.6*	*-7.3*		*2.2*	*0.3*	

Summing up, this section qualifies and reinforces the key results of section 4. Considering bad news, the evidence predominantly suggests that the price adjustment speed is relatively low for high uncertainty stocks. In the case of positive news the opposite conclusions holds.

5.3 Robustness

As in section 4, the above results proved to be robust along various dimensions. First, the good and bad news portfolios were redefined based on earnings surprises, computed as actual announcements of quarterly earnings minus the average of analyst forecasts recorded in the previous month (see section 3 for details on the definition). In this case, we focus on stocks whose immediate reaction is in line with the news, following the logic described in section 4. Tables A.3 and A.4 in the appendix replicate tables 5 and 6 with this alternative measure of the effect of the news; the main messages summarized above are confirmed. This represents a strong robustness check, as the number of observations in the average portfolio drops by 40 to 50 percent, depending on the proxy considered. Other checks yield qualitatively unchanged results (not reported). Abnormal returns were computed as in section 4 (the stock return over the relevant period minus the value-weighted market return in the same period), or as beta-adjusted abnormal returns, as in DellaVigna and Pollet (2009). Moreover, we split our 1985-2005 sample period into two subsamples of equal length. Third, we computed delayed returns over the two or three months following the earnings announcement. Fourth, we pooled stocks in the first and second uncertainty quintiles, and analyzed their behavior vis-à-vis those in the fourth and fifth quintiles.

6. Asymmetric responses to good versus bad news

So far, we have focused on differences in price continuation patterns and adjustment speed across high vs. low uncertainty stocks. The other main cut emerging from our results concerns the bad vs. good news portfolios. Consider the results obtained with the PEAD data (table 6). Among low uncertainty stocks, the shares for the bad news groups are larger than for the good news group in five out of six cases, and significantly so in two (panel B). This suggests that the adjustment speed tends to be the same across good and bad news, or to be relatively low for the latter group. For the high uncertainty portfolios the shares are always significantly larger for the bad news groups. This evidence is reinforced further by the median-based estimators in panels C and D: now the difference $\rho^G - \rho^B$ is negative for both the low and the high uncertainty stocks, and consistently significant for the latter group.[19]

The evidence from analyst forecast revisions (table 3) is in line with these findings for the high uncertainty portfolios. For the low uncertainty portfolios, both the median- and mean-based estimators predominantly suggest that the speed of adjustment is the same across good and bad news.

Summing up, this evidence strongly suggests that the prices of high uncertainty stocks adjust to good news more rapidly than to bad news. For the low uncertainty stocks, the evidence in favor of such conclusion is weaker.

7. Summary evidence and discussion

In this section we first summarize the evidence presented thus far, extracting the "stylized facts" emerging from the previous two sections. Next, we provide a discussion of two possible determinants of these facts.

7.1 Summary evidence

We now resort to a principal component analysis to extract a common factor from our uncertainty proxies. Stocks are then sorted and divided into uncertainty quintiles based on this common factor, and the usual analysis of the four portfolios (good vs. bad news, high vs. low

[19] The ρs estimated as ratio of means (panel A) yield mixed results for the low uncertainty portfolios: three proxies signal that the adjustment speed is higher in the case of bad news, one suggests the opposite, two suggest no difference. By contrast, for the high uncertainty portfolios four out of six proxies support the conclusion that the adjustment to good news is faster, the remaining two yield non significant statistics.

uncertainty) is performed. The procedure is repeated for the two news used above: analyst forecasts revisions and earnings announcements. The results are reported in table 7.[20]

While based on a new indicator of uncertainty, the table is consistent with the evidence of the previous sections, and it serves as a useful summary of the results seen thus far. The shares and the median-based measures of adjustment speed, in panels B through D, suggest the following conclusions: (i) the prices of high uncertainty firms tend to react to bad news more slowly than those of low uncertainty firms; (ii) the prices of high uncertainty firms tend to react to good news with equal speed (according to post-analysts drift data) or more rapidly (according to PEAD data) than those of low uncertainty firms; (iii) among high uncertainty stocks, the price adjustment is faster in the case of good news than in the case of bad news, whereas for the low uncertainty stocks the adjustment speed tends to be more symmetric.

These results are only partly confirmed by the ratio between delayed and immediate mean returns (panel A). As argued above, when conflicting messages emerge from median- and mean-based indicators of adjustment speed, the former should be preferred for our purposes.

Summing up, our findings do not support the popular thesis that price continuation is a consequence of investors' underreaction to news on high uncertainty stocks. In fact, while underreaction – either related to behavioral biases or rational causes – would imply the same negative relationship between stock price adjustment speed and uncertainty regardless of the type of news, we find that the sign of the relationship differs across bad and good news

[20] We use the first common factor of the principal component analysis, which explains about 32 percent of total variation in both datasets. The related loadings are sizeable for all the proxies (no less than 0.37) with the exception of *DISP* (0.04 in both datasets). Considering this fact, and recalling from section 3 that *DISP* is missing by construction for stocks covered by just one or no analysts, which are likely to be opaque, we re-run the principal component analysis based on the other five uncertainty proxies only. The results (not reported) confirm and strengthen the evidence in table 7.

stocks. How does this evidence relate to previous literature, and what interpretation could be consistent with it?

Table 7 - Summary of measures of adjustment speed from sections 4 and 5

(percentage values; t statistics in italics)

The ρ^U measure the ratio between delayed and immediate abnormal stock returns; ρ^U=0 corresponds to immediate price adjustment, positive values to sluggish adjustment, negative values to price reversal. We ran a principal component analysis on our six uncertainty proxies (1/*MV*, 1/*COV*, 1/*AGE*, *SIGMA*, *CVOL, DISP*; see section 3 and the note to table 2 for their definition and construction methodology). Stocks were then sorted and divided into uncertainty quintiles based on the first principal component, which explains 32 per cent of total variation in both datasets, and the usual analysis of the four portfolios (good vs. bad news, high vs. low uncertainty) was performed. The procedure was repeated for our two datasets - the analyst forecasts revisions data and the post-earnings announcement drift (PEAD) data, analyzed in sections 4 and 5, respectively.

News is:	**ANALYST FORECAST REVISIONS**			**QUARTERLY EARNINGS RELEASES (PEAD)**		
	Bad news	Good news	Good - bad	Bad news	Good news	Good - bad
Uncertainty	**Panel A: ρ^U estimated as ratio between delayed and immediate mean abnormal returns**					
Q1 (low)	**-5.21**	**5.64**	**10.85**	**19.55**	**40.48**	**20.93**
	-1.2	*1.4*	*1.5*	*3.1*	*8.0*	*2.1*
Q5 (high)	**0.92**	**8.61**	**7.69**	**39.58**	**27.21**	**-12.37**
	0.3	*3.6*	*1.6*	*5.5*	*4.2*	*-1.0*
Q5-Q1	**6.13**	**2.97**		**20.03**	**-13.27**	
	1.1	*0.6*		*2.1*	*-1.5*	
	Panel B: Share of stocks displaying price continuation					
Q1 (low)	**49.10**	**51.93**	**2.83**	**55.48**	**56.19**	**0.70**
	-0.9	*1.6*	*1.8*	*5.5*	*5.5*	*0.5*
Q5 (high)	**53.57**	**49.35**	**-4.22**	**58.67**	**50.76**	**-7.91**
	3.4	*-0.5*	*-2.7*	*6.8*	*0.7*	*-4.8*
Q5-Q1	**4.47**	**-2.58**		**3.19**	**-5.42**	
	3.1	*-1.5*		*2.0*	*-3.5*	
	Panel C: ρ^U estimated as ratio between delayed and immediate median abnormal returns					
Q1 (low)	**-0.05**	**6.93**	**6.99**	**46.30**	**42.04**	**-4.26**
	0.0	*1.4*	*1.0*	*6.0*	*5.1*	*-0.4*
Q5 (high)	**10.81**	**-2.76**	**-13.57**	**66.74**	**4.97**	**-61.77**
	2.1	*-0.6*	*-1.9*	*7.3*	*0.6*	*-5.2*
Q5-Q1	**10.86**	**-9.70**		**20.44**	**-37.07**	
	1.6	*-1.4*		*1.7*	*-3.3*	
	Panel D: ρ^U estimated as median of ratios between delayed and immediate abnormal returns					
Q1 (low)	**-1.94**	**4.50**	**6.45**	**32.30**	**32.44**	**0.14**
	-1.6	*1.4*	*3.3*	*10.5*	*4.3*	*0.0*
Q5 (high)	**10.06**	**0.50**	**-9.56**	**62.07**	**3.65**	**-58.43**
	6.5	*0.2*	*-4.8*	*20.3*	*0.5*	*-13.4*
Q5-Q1	**12.01**	**-4.00**		**29.77**	**-28.80**	
	6.9	*-1.8*		*6.8*	*-6.7*	

7.2 Short-sale constraints

One theory with implications for price continuation patterns and adjustment speed is the Miller (1977) "divergence of opinion premium" hypothesis. By keeping pessimistic investors out of the market, short sale constraints should prevent negative information from being fully impounded into prices, yielding higher stock valuations and lower future returns. Miller argues that the effect should be proportional to the divergence of opinions among investors about the stock's valuation, which is related to the uncertainty which we try to measure with our proxies.

There is an ample and controversial literature on this overvaluation effect. The empirical evidence is mixed.[21] Its theoretical foundations have been questioned by Diamond and Verrecchia (1987), who show that the effect need not hold under rational expectations. Their model predicts that short sale constraints should slow down stock price reaction to *private* information, and that the adjustment speed should be relatively low in case of bad news. Beber and Pagano (2010) find broad support for these predictions, and survey several other supporting empirical papers. Boehmer and Wu (2010) show that short sale constraints increase price delays (in particular, an above-median shorting activity tends to eliminate the post-earnings announcement drift for the most negative quartile of earnings surprises). However, much of this evidence is based on the time series properties of returns (e.g. autocorrelation patterns) during periods with and without short sale constraints, and therefore it is ill-suited to assess how the release of public information affects stock prices.

[21] Chang, Cheng and Yu (2007) find that the removal of the short sale constraint on individual stocks traded on the Hong Kong market is associated with statistically significant post-event declines in cumulative abnormal returns, and that this pattern is more pronounced for stocks characterized by large dispersion in investor opinions about valuation (measured by proxies akin to our DISP). Other papers are less supportive of this hypothesis. Exploiting the experience of the recent financial crisis, Beber and Pagano (2010) find that the adoption of a short sale ban had a positive effect on stock prices in the US, in line with the Miller effect, but not in all the other 29 countries in their sample. They argue that the US result might be spurious, being influenced by the concomitant announcement of policy measures aimed at supporting financial institutions.

To assess whether short sale constraints may be important determinants of our results we look at three types of evidence. First, the Diamond and Verrecchia (1987) model also yields one prediction concerning *public* information releases in the presence of short sale constraints: they should cause a large immediate absolute stock prices reaction, relative to the no constraints case.[22] Indeed, the evidence in tables 2 and 5 is coherent with this theory, to the extent that our measures of uncertainty are also proxying for the difficulty of shorting stocks. However, we also saw in figures 2 and 3 that the relatively large immediate response of high uncertainty stocks is apparently reflecting relatively large shocks.

Second, if short sale constraints were an important driver of patterns (i)-(iii) illustrated above, we should detect differences in these patterns across stocks that are relatively hard to short vs. those that are easy to short. To explore this possibility, using the quarterly earnings release data we first pooled stocks in the fourth and fifth market capitalization quintiles (first and second quintiles of $1/MV$), which should typically be more liquid and less affected by short-selling constraints,[23] and analyzed their behavior according to our other five uncertainty proxies. We then contrasted these results with those obtained when pooling stocks in the first and second market capitalization quintiles. We find that our results (i) through (iii) are confirmed both among small and large firms (results not reported).

Third, we check whether the delayed returns following quarterly earnings surprises are affected by a downward drift, regardless of the news type affecting the stock at time T. Diether, Malloy and Scherbina (2002) form portfolios of stocks based on the dispersion in analyst earnings forecasts (without conditioning to good or bad news), and find that higher dispersion in a given month is associated with lower returns the following month. They

[22] The intuition is that when public information is released, stock prices “make up” for the relatively slow adjustment to private information experienced in previous periods. Reed (2007) confirms this prediction using quarterly earnings surprises.

[23] Small firm stocks are arguably hardest to short and least likely to have traded options. There is evidence that firm size is directly related to short selling (D’Avolio (2002)).

interpret this evidence as supporting the Miller overvaluation hypothesis. To check whether a similar effect may be at work in our case, we look at the behavior of stocks in the "no news" group (those recording an absolute value of $r^{j}_{T-1,T+1}$ of less than 0.5 percent), which we have overlooked thus far. In principle, since these are "no news" stocks by definition, on average they should record no delayed reaction. It turns out that the return of these stocks in the month following the portfolio formation is close to zero for the low uncertainty portfolios (-0.02 percent on average across our six uncertainty proxies), whereas it is negative (-0.44 percent) for the high uncertainty portfolios. This suggests that high uncertainty stock prices are indeed subject to a (small) downward drift, which seems to be unrelated to the news release.

Summing up, these pieces of evidence suggest that short sale constraints are unlikely to be the main determinants of our results, but do not allow us to rule out this hypothesis. The presence of a negative post-event drift among the no-news, high uncertainty portfolios of stocks indicates that some effect is at work which is not strictly related to news releases. D'Avolio (2002) argues that short sale costs tend to be increasing in the divergence of opinion among investors about a stock's valuation. Thus, to the extent that uncertainty about a stock's valuation translates into divergence of opinion among investors, all our six measures of uncertainty might also be proxying for short sale constraints.[24] Further work on this issue requires more precise measures of short sales constraints.

7.3 Managers' discretion

An alternative mechanism which could rationalize our findings is related to managers' incentives and degree of discretion in managing information flows. Hong, Lim and Stein (2000) show that momentum among small firms or firms with low analyst coverage mainly

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[24] See the discussion and the references in Diether, Malloy and Scherbina (2002)).

stems from the "losers" portfolio, and argue that "bad news travels slowly", especially for high uncertainty firms. This is in line with our finding (i). Finding (ii) supports the complementary hypothesis, i.e. that "good news travels fast", especially for high uncertainty firms. This hypothesis is also suggested by Hong, Lim and Stein (2000): "Think of a firm that has no analyst coverage but is sitting on good news. To the extent that its managers prefer higher to lower stock prices, they will push the news out the door themselves, via increased disclosures, etc." DellaVigna and Pollet (2009) rationalize the slow impact of new information on stock prices using a model where short-term-oriented managers choose to release bad news on days when the fraction of distracted investors is high (Fridays in their analysis), so as to defuse their negative impact. This clearly implies that the same managers choose to release good news on "normal" days, when the price response is more immediate.

The model proposed by DellaVigna and Pollet does not distinguish between high and low uncertainty stocks, but its mechanism could explain the different response to good vs. bad news which we document across these two groups if one is willing to accept the view that managers at less transparent firms have more leeway to manage information flows. In other words, assume that managers like to defuse bad news and anticipate good news, as argued by DellaVigna and Pollet,[25] and that managers of high uncertainty firms enjoy more discretion in managing the release of information, as suggested by Hong, Lim and Stein (2000). These two assumptions should have the following implications: (a) bad news should travel more slowly for high uncertainty stocks than for low uncertainty stocks; (b) good news should travel with equal speed among low uncertainty and high uncertainty stocks, or possibly more rapidly among the latter; (c) bad news should travel more slowly than good news for high uncertainty stocks. Clearly, these implications coincide with our results (i)-(iii) above.

[25] The literature on managers incentives to communicate news to the market provides support for this view. For instance, Kothari, Shu and Wysocki (2008) find evidence that managers tend to delay the release of bad news to investors.

To assess whether managers' discretion in the release of information flows is indeed an important determinant of our results we use analyst forecast errors, as defined in section 3. In section 5.3, devoted to the robustness checks, these errors have been used as an alternative measure of news. Here we exploit the fact that small forecast errors have also been interpreted as evidence of earnings management. The idea is that managers who adopt this practice will tend to release earnings figures that meet or moderately exceed analyst forecasts.[26] Therefore, for each of the bad and good news portfolios we divide stocks into two groups: those whose forecast error is between zero and 0.001 (the "high earnings management" group) and all the remaining stocks ("low earnings management"). We then compute our price sluggishness indicators for the bad-versus-good news, low-versus-high earnings management portfolios, as in section 5. Table A.5 in the appendix, whose format is analogous to table 7, shows that the results (i)-(iii) above are all confirmed, once "uncertainty" is replaced with "earnings management".

This evidence suggests that firms' opaqueness, coupled with managers' incentives, may indeed be an important determinant of the bad-versus-good news adjustment speed asymmetry we find in the data. Further research on discriminating among the possible causes of investors' underreaction to news lies outside the scope of the present paper, but it certainly seems warranted.

[26] Degeorge, Patel and Zeckhauser (1999) show that the distribution of analyst forecast errors presents two asymmetries. First, there is a smaller mass to the left of zero, compared to the right. Second, the right tail is thinner than the left tail. They argue that the first asymmetry reflects firms that, facing actual earnings slightly below analysts' consensus forecast, decide to adjust the figure to be published to match the forecast (these firms "borrow for a better today"). The second asymmetry reflects firms that, facing actual earnings largely above analysts' consensus forecast, decide to adjust the published figure downwards (these firms "save for a better tomorrow"). Recent studies show that these asymmetries are related to balance sheet measures of earnings management, such as abnormal accruals (see e.g. Burgstahler and Eames (2006)).

8. Conclusions

A well-documented anomaly of stock prices is continuation – the fact that future stock returns are predictable based on public information. Attempts at explaining this anomaly have relied on behavioral theories, which suggest that investors suffer from cognitive biases and underreact to new information; alternatively, on theories of rational investors subject to uncertainty, or with constrained attention resources.

The present paper argues that these theories yield sharp testable implications concerning the speed with which stock prices adjust to the arrival of news, and not concerning price continuation patterns, i.e. on the absolute magnitude of the delayed stock return. Specifically, if the behavioral theories of stock price underreaction are correct, and if behavioral biases are heightened by uncertainty surrounding the firm, as argued by several recent papers, then the speed with which stock prices adjust to news should be inversely related to the degree of uncertainty, whereas the magnitude of the delayed return (may but) need not. To test whether different groups of stocks are characterized by different price underreaction patterns to news, one must therefore measure adjustment speed, not price continuation patterns, on which the literature has focused thus far.

To this end we use two different news types, which give rise to well-documented instances of price continuation: the post-analyst revisions price drift and the post-earnings announcement drift (PEAD). We form portfolios of high and low uncertainty stocks, using several commonly used proxies for uncertainty. Then, for each portfolio and news type, we compute various alternative estimators of adjustment, speed that do not depend on the scale of the news. A broadly coherent picture emerges from the evidence presented in the paper, which can be summarized as follows.

First, based on the two measures of news considered (analyst forecasts revisions and quarterly earnings surprises), we find that the high price continuation documented in previous literature for high uncertainty stocks is largely due to the fact that these stocks are subject to "larger news"; hence, both their immediate and delayed mean price reactions tend to be larger, in absolute value, than for low uncertainty stocks. Thus, higher price continuation need not imply slower adjustment, nor does higher uncertainty.

Second, based on the same two news types, our median-based measures of adjustment speed (e.g. the ratio between delayed and immediate median returns) yield the following regularities: (i) the prices of high uncertainty firms tend to react to *bad* news more slowly than those of low uncertainty firms; (ii) the prices of high uncertainty firms tend to react to *good* news with equal speed or more rapidly than those of low uncertainty firms; (iii) the prices of high uncertainty stocks adjust to good news more rapidly than to bad news.

The mean-based measure of adjustment speed (the ratio between delayed and immediate *mean* returns) does not yield clearcut results. To the extent that, when discussing high vs. low uncertainty stocks, one has in mind a "representative" stock for each category, we argue that median-based measures, although not commonly used in the literature, should be preferred.

Summing up, information opacity has an effect on stock price adjustment speed, but this effect differs across bad and good news portfolios. This is not in line with the hypothesis, which we set out to test, that high uncertainty firms should be characterized by slower stock price reaction to news *regardless* of the type of news. Recent theories and findings about managers' incentives and investors' limited attention may rationalize our results (i) through (iii). Specifically, if managers like to defuse bad news and anticipate good news, and if managers at high uncertainty firms enjoy relatively more discretion about the release of information, as suggested by several recent papers, then one should expect to see the patterns which we detect in the data. Short sale constraints are also known to influence stock price adjustment speed. The checks that we perform suggest that they are unlikely to be the main determinants of our results, but we cannot rule out their influence. Further empirical research could be devoted to confirming or disproving the generality of our findings (e.g. using additional measures of informational uncertainty, or different news events), and to a more thorough study of their determinants.

References

Barberis, N., A. Shleifer and R. Vishny (1998), "A model of investor sentiment", Journal of Financial Economics, 49, 307-343.

Beber, A. and M. Pagano (2010), "Short-selling bans around the world: evidence from the 2007-09 crisis", CEPR discussion paper no. 7557.

Bernard, V., and J. Thomas (1989), "Post-earnings announcement drift: Delayed price response or risk premium?" Journal of Accounting Research, 27, 1-36.

Bernard, V., and J. Thomas (1990), "Evidence that stock prices do not fully reflect the implications of current earnings for future earnings", Journal of Accounting and Economics, 13, 305-340.

Boehmer, E. and J. Wu (2010), "Short selling and the price discovery process", mimeo.

Brav, A., and J. B. Heaton (2002), "Competing theories of financial anomalies", The Review of Financial Studies, 15, 575-606.

Brown, S. J. and J. B. Warner (1985), "Using daily stock returns: The case of event studies", Journal of Financial Economics, 14, 3-31.

Burgstahler, D. and M. Eames (2006), "Management of earnings and analysts' forecasts to achieve zero and small positive earnings surprises", Journal of Business Finance and Accounting, 33, 633-652.

Campbell, J. Y., A. Lo and A. C. MacKinlay (1997), "The econometrics of financial markets", Princeton University Press, Princeton NJ.

Carhart, M., (1997), "On persistence in mutual fund performance", The Journal of Finance, 52, 57-82.

Chan, L. K. C., N. Jegadeesh and J. Lakonishok (1996), "Momentum strategies", The Journal of Finance, 51, 1681-1713.

Chang, E. C., J. W. Cheng and Y. Yu, (2007), "Short-sales constraints and price discovery: Evidence on the Hong Kong market", The Journal of Finance, 57, 2097-2121.

Conrad, J., B. Cornell and W.R. Landsman (2002), "When is bad news really bad news?", The Journal of Finance, 57, 2507-2532.

Daniel, K., D. Hirshleifer, and A. Subrahmaniam (1998), "Investor psychology and security market over- and under-reactions", The Journal of Finance, 53, 1839-1886.

Daniel, K., D. Hirshleifer, and A. Subrahmaniam (2001), "Overconfidence, arbitrage and equilibrium asset pricing", The Journal of Finance, 56, 921-965.

D'Avolio, G. (2002), "The market for borrowing stock", Journal of Financial Economics, 66, 271-306.

Degeorge, F., J. Patel and R. Zeckhauser (1999), "Earnings management to exceed threshold", The Journal of Business, 72, 1-33.

DellaVigna, S. and J. M. Pollet (2009), "Investor inattention and Friday earnings announcements", The Journal of Finance, 64, 709-749.

Diamond, D. W. and R. E. Verrecchia (1987), "Constraints on short selling and asset price adjustment to private information", Journal of Financial Economics, 18, 277-311.

Diether, K. B., C. J. Malloy and A. Scherbina (2002), "Differences of opinion and the cross section of stock returns", The Journal of Finance, 57, 2113-2141.

Fama, E. (1998), "Market efficiency, long-term returns, and behavioral finance", Journal of Financial Economics, 49, 283-306.

Fama, E. and K. French (1996), "Multifactor explanations of asset pricing anomalies", The Journal of Finance, 51, 55-84.

Frazzini, A. (2006), "The disposition effect and underreaction to news", The Journal of Finance, 61, 2017-2046.

Gleason, C. A. and C. M. C. Lee (2003), "Analyst Forecast Revisions and Market Price Discovery", The Accounting Review, 78, 193-225.

Hirshleifer, D. (2001), "Investor Psychology and Asset Pricing", The Journal of Finance, 56, 1533-1597.

Hirshleifer, D., S. Seongyeon Lim and S. Hong Teoh (2007), "Driven to Distraction: Extraneous Events and Underreaction to Earnings News", The Journal of Finance, 64, 2289-2325.

Hong, H. and J. Stein (1999), "A unified theory of underreaction, momentum trading and overreaction in asset markets", The Journal of Finance, 54, 2143-2184.

Hong, H. T. Lim and J. Stein (2000), "Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies", The Journal of Finance, 55, 265-295.

Hou, K. and T. J. Moskowitz (2005), "Market frictions, Price delay, and the cross section of expected returns", The Review of Financial Studies, 18, 981-1020.

Huang, L. and Hong Liu (2007), "Rational inattention and portfolio selection", The Journal of Finance, 57, 1999-2040.

Jackson, A. and T. Johnson (2006), "Unifying underreaction anomalies", The Journal of Business, 79, 75-114.

Jegadeesh, N. and S. Titman (1993), "Returns to buying winners and selling losers: Implications for stock market efficiency", The Journal of Finance, 48, 65-91.

Jegadeesh, N. and S. Titman (2001), "Profitability of Momentum Strategies: An Evaluation of Alternative Explanations", The Journal of Finance, 56, 699-720.

Kothari, S. P., S. Shu and P. Wysocki (2008), "Do managers withhold bad news?", mimeo.

Loh, R. K. and R. M. Stulz (2009), "When are analyst recommendation changes influential?" NBER Working Paper 14971.

Masulis, R. W. and L. Shivakumar (2002), "Does Market Structure Affect the Immediacy of Stock Price Responses to News?", The Journal of Financial and Quantitative Analysis, 37, 617-648.

Miller, E. M. (1977), "Risk, uncertainty and divergence of opinion", The Journal of Finance, 32, 1151-1168.

Peng, L. (2005), “Learning with information capacity constraints”, Journal of Financial and Quantitative Analysis, 40, 307-330.

Peng, L. and W. Xiong (2006), “Investor attention, overconfidence and category learning”, Journal of Financial Economics, 80, 563-302.

Reed, A. V. (2007), “Costly short selling and stock prices adjustment to earnings announcements”, mimeo.

Stickel, S. E. (1991), “Common Stock Returns Surrounding Earnings Forecast Revisions: More Puzzling Evidence”, The Accounting Review, 66, 402-416.

Thaler, R. H. (ed.) (1993), “Advances in behavioral finance”, Russell Sage, New York.

Trueman, B. (1994), “Analyst forecasts and herding behavior”, The Review of Financial Studies, 7, 97-124.

Zhang, X. Frank, (2006), “Information uncertainty and stock returns”, The Journal of Finance, 61, 105-137.

Table A.1 - Average abnormal returns and information uncertainty
News: analyst forecast revision. All observations

(percentage values; t statistics in italics)

The table is the analogue to table 2, except that stocks whose current return was inconsistent with the news (those recording a negative analyst forecast revision and a positive return, or those recording a positive analyst forecast revision and a negative return) are now kept in the dataset. For each month *T* in the sample we partition stocks into 3 groups, depending on whether the forecast revision in *T* is positive, zero or negative. Within the positive and negative forecast revision groups we then sort stocks into 5 quintiles, based on six proxies for information uncertainty measured in *T*, and compute average returns for each quintile over the 1985-2005 period. Panel A reports returns in *T*; returns in *T*+1 are in panel B. t statistics, in italics, are robust to heteroskedasticity and to clustering within periods. See Section 3 and the note to table 2 for details.

Panel A: Abnormal returns in the month of the positive or negative forecast revision

	Sorted by 1/MV				*Sorted by 1/COV*				*Sorted by 1/AGE*			
Uncertainty	Bad news	Good new	Good - bad		Bad news	Good new	Good - bad		Bad news	Good news	Good - bad	
Q1 (low)	**-0.13**	**2.32**	**2.45**	*17.7*	**-1.03**	**2.55**	**3.57**	*18.3*	**-0.98**	**2.32**	**3.30**	*19.8*
Q2	**-0.58**	**3.02**	**3.59**	*19.5*	**-1.25**	**2.83**	**4.08**	*21.2*	**-1.15**	**3.00**	**4.15**	*22.3*
Q3	**-0.98**	**3.70**	**4.67**	*22.6*	**-1.51**	**3.44**	**4.95**	*24.1*	**-1.43**	**3.54**	**4.98**	*22.7*
Q4	**-2.04**	**4.00**	**6.05**	*25.6*	**-1.86**	**3.94**	**5.80**	*26.7*	**-1.62**	**4.20**	**5.82**	*28.5*
Q5 (high)	**-3.43**	**3.91**	**7.34**	*31.2*	**-1.50**	**4.43**	**5.92**	*26.3*	**-2.01**	**4.00**	**6.01**	*26.7*
Q5-Q1	**-3.30**	**1.59**			**-0.47**	**1.88**			**-1.04**	**1.68**		
	-10.8	*5.0*			*-1.8*	*6.8*			*-2.7*	*4.3*		
	Sorted by SIGMA				*Sorted by CVOL*				*Sorted by DISP*			
	Bad news	Good new	Good - bad		Bad news	Good new	Good - bad		Bad news	Good news	Good - bad	
Q1 (low)	**-0.58**	**1.48**	**2.07**	*18.0*	**-0.70**	**1.98**	**2.67**	*15.8*	**-0.97**	**2.50**	**3.46**	*19.9*
Q2	**-0.89**	**2.20**	**3.09**	*19.3*	**-1.23**	**2.57**	**3.81**	*21.2*	**-1.02**	**2.88**	**3.90**	*18.9*
Q3	**-1.34**	**3.13**	**4.47**	*23.4*	**-1.54**	**3.52**	**5.06**	*23.0*	**-1.34**	**3.23**	**4.58**	*23.5*
Q4	**-1.79**	**4.16**	**5.95**	*24.4*	**-1.61**	**4.01**	**5.61**	*21.5*	**-1.72**	**3.48**	**5.20**	*24.0*
Q5 (high)	**-2.52**	**6.00**	**8.52**	*26.5*	**-1.39**	**4.86**	**6.25**	*22.5*	**-2.31**	**4.37**	**6.69**	*22.9*
Q5-Q1	**-1.94**	**4.52**			**-0.69**	**2.89**			**-1.35**	**1.88**		
	-3.0	*6.5*			*-1.5*	*6.3*			*-4.4*	*6.7*		

Panel B: Abnormal returns in the month following the forecast revision

	Sorted by 1/MV				*Sorted by 1/COV*				*Sorted by 1/AGE*			
Uncertainty	Bad news	Good new	Good - bad		Bad news	Good new	Good - bad		Bad news	Good news	Good - bad	
Q1 (low)	**-0.03**	**0.41**	**0.44**	*3.4*	**0.05**	**0.56**	**0.51**	*2.8*	**0.00**	**0.56**	**0.56**	*3.7*
Q2	**0.00**	**0.37**	**0.37**	*2.0*	**-0.07**	**0.47**	**0.54**	*3.0*	**-0.05**	**0.99**	**1.04**	*6.3*
Q3	**-0.14**	**0.82**	**0.96**	*4.9*	**-0.17**	**0.78**	**0.95**	*5.2*	**-0.16**	**1.00**	**1.16**	*6.6*
Q4	**-0.27**	**1.16**	**1.42**	*7.2*	**-0.35**	**1.17**	**1.52**	*7.9*	**-0.21**	**1.11**	**1.32**	*6.9*
Q5 (high)	**-0.57**	**1.78**	**2.35**	*13.7*	**-0.48**	**1.71**	**2.19**	*13.4*	**-0.60**	**0.92**	**1.52**	*7.8*
Q5-Q1	**-0.54**	**1.37**			**-0.53**	**1.15**			**-0.60**	**0.36**		
	-1.9	*4.7*			*-2.2*	*4.3*			*-1.6*	*0.9*		
	Sorted by SIGMA				*Sorted by CVOL*				*Sorted by DISP*			
	Bad news	Good new	Good - bad		Bad news	Good new	Good - bad		Bad news	Good news	Good - bad	
Q1 (low)	**0.11**	**0.64**	**0.53**	*4.8*	**0.12**	**0.81**	**0.70**	*5.2*	**-0.19**	**0.68**	**0.87**	*5.0*
Q2	**-0.02**	**0.76**	**0.78**	*6.1*	**-0.08**	**0.78**	**0.87**	*5.6*	**0.01**	**0.64**	**0.63**	*3.4*
Q3	**-0.14**	**0.93**	**1.07**	*6.3*	**-0.10**	**0.76**	**0.86**	*4.5*	**-0.06**	**0.75**	**0.81**	*5.1*
Q4	**-0.32**	**1.10**	**1.42**	*7.0*	**-0.11**	**0.95**	**1.06**	*5.1*	**-0.29**	**0.97**	**1.26**	*7.0*
Q5 (high)	**-0.62**	**1.11**	**1.73**	*6.0*	**0.04**	**1.22**	**1.18**	*4.5*	**-0.30**	**1.08**	**1.38**	*5.8*
Q5-Q1	**-0.73**	**0.47**			**-0.07**	**0.41**			**-0.11**	**0.41**		
	-1.2	*0.7*			*-0.2*	*0.9*			*-0.5*	*1.5*		

Table A.2 - Stock price sluggishness and information uncertainty News: sign of return in the month of analyst forecasts revision

(percentage values; t statistics in italics)

The table is the analogue to table 3, except that bad and good news portfolios are constructed based on the sign of the return in the month of the analyst earnings forecasts revision. Specifically, the good (bad) news portfolios comprise stocks which, in month *T*, record a nonzero revision of the average analyst forecast and an immediate return r_T^j above 0.5 percent (below -0.5 percent). The Qs denote uncertainty quintiles, computed from independent sortings of the six proxies reported in the table. The ρ^U measure the ratio between delayed and immediate stock returns; ρ^U=0 corresponds to immediate price adjustment, positive values to sluggish adjustment, negative values to price reversal. See section 3 and the notes to tables 2 and 3 for details.

Panel A: ρ^U estimated as ratio between delayed and immediate mean abnormal returns

	Sorted by 1/MV			*Sorted by 1/COV*			*Sorted by 1/AGE*		
Uncertainty	Bad news	Good news	Good - bad	Bad news	Good news	Good - bad	Bad news	Good news	Good - bad
Q1 (low)	**-2.34**	**1.59**	**3.93**	**-2.80**	**3.01**	**5.81**	**-2.20**	**3.78**	**5.98**
	-1.0	*0.8*	*1.8*	*-1.0*	*1.5*	*1.6*	*-0.6*	*1.4*	*1.1*
Q5 (high)	**-1.44**	**3.43**	**4.87**	**-2.36**	**3.56**	**5.91**	**1.65**	**0.81**	**-0.84**
	-0.5	*1.7*	*1.1*	*-0.8*	*1.7*	*1.4*	*0.5*	*0.4*	*-0.2*
Q5-Q1	**0.90**	**1.85**		**0.44**	**0.55**		**3.85**	**-2.97**	
	0.3	*0.7*		*0.2*	*0.2*		*0.8*	*-0.9*	
	Sorted by SIGMA			*Sorted by CVOL*			*Sorted by DISP*		
	Bad news	Good news	Good - bad	Bad news	Good news	Good - bad	Bad news	Good news	Good - bad
Q1 (low)	**-7.42**	**4.50**	**11.92**	**-8.07**	**3.93**	**12.01**	**-3.74**	**-0.18**	**3.56**
	-1.6	*1.2*	*1.6*	*-2.2*	*1.2*	*2.0*	*-1.3*	*-0.1*	*1.0*
Q5 (high)	**2.37**	**2.52**	**0.15**	**-1.61**	**6.09**	**7.70**	**1.48**	**5.42**	**3.94**
	0.6	*1.0*	*0.0*	*-0.5*	*2.4*	*1.5*	*0.5*	*2.5*	*0.9*
Q5-Q1	**9.79**	**-1.98**		**6.46**	**2.16**		**5.21**	**5.60**	
	1.4	*-0.4*		*1.2*	*0.5*		*1.9*	*2.7*	

Panel B: Share of stocks displaying price continuation

	Sorted by 1/MV			*Sorted by 1/COV*			*Sorted by 1/AGE*		
Uncertainty	Bad news	Good news	Good - bad	Bad news	Good news	Good - bad	Bad news	Good news	Good - bad
Q1 (low)	**49.93**	**49.40**	**-0.53**	**50.13**	**49.74**	**-0.39**	**50.60**	**49.63**	**-0.97**
	-0.1	*-1.0*	*-0.6*	*0.2*	*-0.4*	*-0.4*	*0.8*	*-0.5*	*-0.9*
Q5 (high)	**52.64**	**45.87**	**-6.77**	**51.80**	**46.46**	**-5.34**	**51.70**	**47.10**	**-4.60**
	3.2	*-5.3*	*-6.0*	*2.2*	*-4.6*	*-4.7*	*2.3*	*-4.0*	*-4.4*
Q5-Q1	**2.71**	**-3.53**		**1.68**	**-3.28**		**1.10**	**-2.54**	
	2.6	*-3.5*		*1.5*	*-3.3*		*1.0*	*-2.5*	
	Sorted by SIGMA			*Sorted by CVOL*			*Sorted by DISP*		
	Bad news	Good news	Good - bad	Bad news	Good news	Good - bad	Bad news	Good news	Good - bad
Q1 (low)	**48.96**	**49.35**	**0.40**	**47.80**	**48.69**	**0.90**	**49.18**	**48.16**	**-1.02**
	-1.2	*-0.8*	*0.3*	*-2.2*	*-1.3*	*0.6*	*-1.2*	*-2.8*	*-1.1*
Q5 (high)	**53.51**	**45.96**	**-7.56**	**52.82**	**48.33**	**-4.50**	**51.90**	**48.32**	**-3.58**
	3.6	*-4.7*	*-5.8*	*3.1*	*-1.9*	*-3.6*	*2.2*	*-2.1*	*-3.0*
Q5-Q1	**4.56**	**-3.40**		**5.03**	**-0.36**		**2.71**	**0.16**	
	3.5	*-2.8*		*3.8*	*-0.3*		*2.4*	*0.2*	

(Table A.2 contd.)

Panel C: ρ^U estimated as ratio between delayed and immediate median abnormal returns

	Sorted by 1/MV			*Sorted by 1/COV*			*Sorted by 1/AGE*		
Uncertainty	Bad news	Good news	Good - bad	Bad news	Good news	Good - bad	Bad news	Good news	Good - bad
Q1 (low)	**0.42**	**-1.18**	**-1.60**	**0.76**	**-0.31**	**-1.06**	**1.52**	**-2.56**	**-4.08**
	0.2	*-0.6*	*-0.5*	*0.3*	*-0.2*	*-0.3*	*0.5*	*-1.1*	*-1.1*
Q5 (high)	**7.84**	**-17.40**	**-25.24**	**6.89**	**-11.98**	**-18.88**	**7.00**	**-9.05**	**-16.05**
	2.7	*-5.7*	*-6.0*	*2.4*	*-4.5*	*-4.8*	*2.5*	*-3.7*	*-4.4*
Q5-Q1	**7.42**	**-16.22**		**6.14**	**-11.67**		**5.47**	**-6.50**	
	2.0	*-4.4*		*1.6*	*-3.6*		*1.4*	*-1.9*	
	Sorted by SIGMA			*Sorted by CVOL*			*Sorted by DISP*		
	Bad news	Good news	Good - bad	Bad news	Good news	Good - bad	Bad news	Good news	Good - bad
Q1 (low)	**-4.56**	**-4.39**	**0.18**	**-7.74**	**-8.30**	**-0.56**	**-1.90**	**-7.78**	**-5.88**
	-1.3	*-1.3*	*0.0*	*-2.2*	*-1.9*	*-0.1*	*-0.7*	*-3.5*	*-1.7*
Q5 (high)	**10.29**	**-10.61**	**-20.90**	**9.16**	**-4.98**	**-14.14**	**7.63**	**-6.77**	**-14.41**
	3.0	*-3.7*	*-4.7*	*2.8*	*-1.7*	*-3.2*	*2.6*	*-2.6*	*-3.7*
Q5-Q1	**14.85**	**-6.22**		**16.89**	**3.32**		**9.53**	**1.01**	
	3.0	*-1.4*		*3.5*	*0.6*		*2.4*	*0.3*	

Panel D: ρ^U estimated as median of ratios between delayed and immediate abnormal returns

	Sorted by 1/MV			*Sorted by 1/COV*			*Sorted by 1/AGE*		
Uncertainty	Bad news	Good news	Good - bad	Bad news	Good news	Good - bad	Bad news	Good news	Good - bad
Q1 (low)	**-0.89**	**-1.28**	**-0.38**	**0.08**	**-0.80**	**-0.89**	**1.28**	**0.15**	**-1.14**
	-1.0	*-0.6*	*-0.3*	*0.1*	*-0.4*	*-0.8*	*1.5*	*0.1*	*-0.9*
Q5 (high)	**7.08**	**-5.05**	**-12.13**	**3.92**	**-3.74**	**-7.67**	**5.62**	**-4.84**	**-10.45**
	7.7	*-2.3*	*-9.8*	*4.3*	*-1.8*	*-6.0*	*6.2*	*-2.3*	*-8.3*
Q5-Q1	**7.97**	**-3.77**		**3.84**	**-2.94**		**4.33**	**-4.98**	
	6.5	*-3.0*		*3.2*	*-2.4*		*3.6*	*-4.0*	
	Sorted by SIGMA			*Sorted by CVOL*			*Sorted by DISP*		
	Bad news	Good news	Good - bad	Bad news	Good news	Good - bad	Bad news	Good news	Good - bad
Q1 (low)	**-1.92**	**0.84**	**2.76**	**-3.85**	**1.47**	**5.31**	**-1.39**	**-3.41**	**-2.03**
	-2.2	*0.4*	*2.3*	*-3.7*	*0.6*	*3.7*	*-1.6*	*-1.6*	*-1.6*
Q5 (high)	**11.64**	**-4.96**	**-16.60**	**7.28**	**-1.90**	**-9.18**	**6.85**	**-1.77**	**-8.62**
	13.4	*-2.4*	*-13.9*	*7.1*	*-0.8*	*-6.4*	*7.6*	*-0.8*	*-7.0*
Q5-Q1	**13.56**	**-5.80**		**11.13**	**-3.37**		**8.23**	**1.64**	
	11.4	*-4.7*		*7.8*	*-2.3*		*6.7*	*1.3*	

Table A.3 - Average abnormal stock returns and information uncertainty
News: analyst forecast errors of quarterly earnings

(percentage values; t statistics in italics)

The table is the analogue to table 5, except that bad and good news portfolios are constructed based on analyst forecasts errors, computed as actual quarterly earnings per share minus their expected value based on average analyst forecasts, normalized by the stock's lagged price (see section 3 for details). The Qs denote uncertainty quintiles, computed from independent sortings of the six proxies reported in the table. Abnormal returns are computed using the market model, as described in section 5. The heteroskedasticity robust t statistics, in italics, are obtained by regressing individual stock returns on a set of ten dummy variables, one for each quintile-news pair, allowing for clustering at the date level. We dropped stocks whose immediate abnormal return was inconsistent with the news, i.e. stocks with positive immediate (negative) returns for the formation of the bad (good) news portfolios. See Section 3 and the note to table 5 for details.

Panel A: Abnormal returns in the 3-day window around negative or positive earnings surprises

	Sorted by 1/MV				*Sorted by 1/COV*				*Sorted by 1/AGE*			
Uncertainty	Bad news	Good news	Good - bad		Bad news	Good news	Good - bad		Bad news	Good new	Good - bad	
Q1 (low)	**-3.96**	**4.04**	**8.00**	*30.2*	**-4.82**	**4.92**	**9.74**	*32.2*	**-3.74**	**4.00**	**7.73**	*34.0*
Q2	**-4.91**	**4.89**	**9.79**	*31.7*	**-5.44**	**5.36**	**10.80**	*33.4*	**-4.80**	**4.97**	**9.77**	*36.0*
Q3	**-5.73**	**5.59**	**11.32**	*35.5*	**-5.73**	**5.83**	**11.56**	*38.8*	**-5.58**	**5.68**	**11.26**	*38.5*
Q4	**-6.31**	**6.22**	**12.53**	*43.8*	**-5.79**	**5.80**	**11.59**	*45.8*	**-6.38**	**6.38**	**12.75**	*43.5*
Q5 (high)	**-6.44**	**6.76**	**13.20**	*61.3*	**-5.52**	**5.57**	**11.09**	*54.5*	**-7.00**	**6.60**	**13.59**	*43.1*
Q5-Q1	**-2.48**	**2.72**			**-0.70**	**0.65**			**-3.26**	**2.60**		
	-24.0	*22.8*			*-5.2*	*5.9*			*-27.4*	*25.2*		
	Sorted by SIGMA				*Sorted by CVOL*				*Sorted by DISP*			
	Bad news	Good news	Good - bad		Bad news	Good news	Good - bad		Bad news	Good new	Good - bad	
Q1 (low)	**-2.77**	**2.96**	**5.72**	*35.6*	**-3.29**	**3.43**	**6.73**	*37.5*	**-5.48**	**5.38**	**10.87**	*33.0*
Q2	**-3.96**	**4.10**	**8.06**	*42.8*	**-4.24**	**4.33**	**8.57**	*37.0*	**-5.44**	**5.25**	**10.68**	*35.4*
Q3	**-5.25**	**5.22**	**10.47**	*37.0*	**-5.09**	**5.21**	**10.30**	*38.1*	**-5.36**	**5.37**	**10.73**	*34.2*
Q4	**-6.70**	**6.76**	**13.46**	*40.2*	**-5.68**	**6.03**	**11.71**	*41.6*	**-5.31**	**5.54**	**10.86**	*39.9*
Q5 (high)	**-8.59**	**8.42**	**17.01**	*39.7*	**-7.10**	**7.06**	**14.16**	*46.5*	**-5.83**	**5.96**	**11.78**	*39.2*
Q5-Q1	**-5.82**	**5.46**			**-3.81**	**3.63**			**-0.34**	**0.57**		
	-29.9	*34.9*			*-24.8*	*34.8*			*-3.3*	*4.4*		

Panel B: Abnormal returns in the month following earnings surprises

	Sorted by 1/MV				*Sorted by 1/COV*				*Sorted by 1/AGE*			
Uncertainty	Bad news	Good news	Good - bad		Bad news	Good news	Good - bad		Bad news	Good news	Good - bad	
Q1 (low)	**-0.80**	**0.53**	**1.33**	*7.3*	**-0.02**	**0.93**	**0.94**	*4.4*	**-0.57**	**1.47**	**2.04**	*10.3*
Q2	**-1.35**	**0.48**	**1.83**	*8.8*	**-0.38**	**1.14**	**1.52**	*6.8*	**-0.75**	**1.16**	**1.91**	*8.8*
Q3	**-1.28**	**0.86**	**2.15**	*8.1*	**-0.67**	**0.95**	**1.62**	*6.4*	**-0.90**	**0.69**	**1.59**	*5.8*
Q4	**-0.92**	**0.95**	**1.87**	*5.9*	**-1.79**	**0.69**	**2.48**	*9.9*	**-1.33**	**0.67**	**2.00**	*7.1*
Q5 (high)	**-0.72**	**1.21**	**1.92**	*6.4*	**-2.62**	**0.32**	**2.94**	*9.0*	**-1.56**	**-0.02**	**1.54**	*5.3*
Q5-Q1	**0.09**	**0.68**			**-2.60**	**-0.60**			**-0.99**	**-1.49**		
	0.2	*1.5*			*-7.0*	*-1.8*			*-2.4*	*-3.1*		
	Sorted by SIGMA				*Sorted by CVOL*				*Sorted by DISP*			
	Bad news	Good news	Good - bad		Bad news	Good news	Good - bad		Bad news	Good new	Good - bad	
Q1 (low)	**-0.48**	**1.45**	**1.93**	*11.1*	**-0.74**	**1.31**	**2.06**	*12.4*	**-0.91**	**0.96**	**1.87**	*7.5*
Q2	**-0.73**	**1.20**	**1.93**	*12.3*	**-0.86**	**1.23**	**2.10**	*8.3*	**-0.70**	**0.98**	**1.68**	*6.4*
Q3	**-0.78**	**1.01**	**1.79**	*8.2*	**-0.86**	**1.20**	**2.06**	*7.8*	**-0.69**	**1.14**	**1.82**	*6.2*
Q4	**-0.98**	**0.89**	**1.86**	*6.1*	**-0.68**	**1.07**	**1.75**	*5.8*	**-0.35**	**0.78**	**1.12**	*4.1*
Q5 (high)	**-2.00**	**-0.47**	**1.53**	*4.1*	**-1.47**	**0.27**	**1.74**	*4.8*	**-0.85**	**0.30**	**1.15**	*3.4*
Q5-Q1	**-1.51**	**-1.92**			**-0.72**	**-1.04**			**0.07**	**-0.66**		
	-2.5	*-3.4*			*-1.6*	*-2.8*			*0.2*	*-2.1*		

Table A.4 - Stock price sluggishness and information uncertainty
News: analyst forecast errors of quarterly earnings

(percentage values; t statistics in italics)

The table is the analogue to table 6, except that bad and good news portfolios are constructed based on analyst forecasts errors, computed as actual quarterly earnings per share minus their expected value based on average analyst forecasts, normalized by the stock's lagged price (see section 3 for details). The Qs denote uncertainty quintiles, computed from independent sortings of the six proxies reported in the table (see the note to table 2 and section 3 for their definition and construction methodology). The ρ^U measure the ratio between delayed and immediate stock returns; ρ^U=0 corresponds to immediate price adjustment, positive values to sluggish adjustment, negative values to price reversal. See Section 3 and the notes to tables 5 and 6 for details.

Panel A: ρ^U estimated as a ratio between delayed and immediate mean abnormal returns

	Sorted by 1/MV			*Sorted by 1/COV*			*Sorted by 1/AGE*		
Uncertainty	Bad news	Good news	Good - bad	Bad news	Good news	Good - bad	Bad news	Good news	Good - bad
Q1 (low)	**20.28**	**13.06**	**-7.22**	**0.38**	**18.82**	**18.43**	**15.20**	**36.90**	**21.70**
	7.6	*5.9*	*-2.1*	*0.1*	*8.9*	*5.4*	*5.5*	*16.7*	*6.2*
Q5 (high)	**11.12**	**17.86**	**6.73**	**47.48**	**5.82**	**-41.67**	**22.31**	**-0.27**	**-22.58**
	4.0	*8.4*	*1.9*	*13.3*	*2.1*	*-9.2*	*8.3*	*-0.1*	*-6.4*
Q5-Q1	**-9.16**	**4.80**		**47.10**	**-13.00**		**7.10**	**-37.17**	
	-2.4	*1.6*		*10.6*	*-3.7*		*1.9*	*-11.6*	
	Sorted by SIGMA			*Sorted by CVOL*			*Sorted by DISP*		
	Bad news	Good news	Good - bad	Bad news	Good news	Good - bad	Bad news	Good news	Good - bad
Q1 (low)	**17.42**	**48.99**	**31.57**	**22.62**	**38.23**	**15.61**	**16.65**	**17.79**	**1.14**
	6.1	*20.5*	*8.5*	*6.4*	*12.9*	*3.4*	*6.1*	*7.3*	*0.3*
Q5 (high)	**23.24**	**-5.58**	**-28.82**	**20.69**	**3.82**	**-16.87**	**14.52**	**5.05**	**-9.47**
	8.8	*-2.6*	*-8.4*	*6.1*	*1.4*	*-3.9*	*4.2*	*1.9*	*-2.2*
Q5-Q1	**5.82**	**-54.57**		**-1.93**	**-34.41**		**-2.13**	**-12.74**	
	1.5	*-16.9*		*-0.4*	*-8.6*		*-0.5*	*-3.5*	

Panel B: Share of stocks displaying price continuation

	Sorted by 1/MV			*Sorted by 1/COV*			*Sorted by 1/AGE*		
Uncertainty	Bad news	Good news	Good - bad	Bad news	Good news	Good - bad	Bad news	Good news	Good - bad
Q1 (low)	**56.20**	**51.96**	**-4.24**	**52.97**	**51.77**	**-1.20**	**55.06**	**53.99**	**-1.07**
	8.5	*2.1*	*-3.6*	*4.1*	*2.4*	*-1.2*	*6.2*	*5.3*	*-1.0*
Q5 (high)	**56.13**	**50.05**	**-6.08**	**60.12**	**49.01**	**-11.11**	**57.41**	**47.31**	**-10.11**
	6.8	*0.0*	*-4.0*	*9.9*	*-1.0*	*-7.6*	*7.8*	*-2.6*	*-7.1*
Q5-Q1	**-0.07**	**-1.91**		**7.15**	**-2.76**		**2.35**	**-6.69**	
	-0.1	*-1.2*		*5.7*	*-2.2*		*1.9*	*-5.2*	
	Sorted by SIGMA			*Sorted by CVOL*			*Sorted by DISP*		
	Bad news	Good news	Good - bad	Bad news	Good news	Good - bad	Bad news	Good news	Good - bad
Q1 (low)	**54.59**	**55.61**	**1.02**	**55.14**	**54.34**	**-0.80**	**55.80**	**51.86**	**-3.94**
	5.0	*5.8*	*0.8*	*5.2*	*3.4*	*-0.5*	*7.0*	*2.0*	*-3.2*
Q5 (high)	**57.81**	**45.00**	**-12.81**	**56.99**	**48.42**	**-8.57**	**55.74**	**49.15**	**-6.60**
	8.0	*-5.1*	*-9.3*	*6.4*	*-1.3*	*-5.3*	*5.4*	*-0.8*	*-4.3*
Q5-Q1	**3.22**	**-10.61**		**1.86**	**-5.92**		**-0.06**	**-2.72**	
	2.4	*-7.7*		*1.3*	*-3.4*		*0.0*	*-1.9*	

(Table A.4 contd.)

Panel C: ρ^U estimated as ratio between delayed and immediate median abnormal returns

	Sorted by 1/MV			*Sorted by 1/COV*			*Sorted by 1/AGE*		
Uncertainty	Bad news	Good news	Good - bad	Bad news	Good news	Good - bad	Bad news	Good news	Good - bad
Q1 (low)	**43.36**	**10.68**	**-32.68**	**19.98**	**10.06**	**-9.92**	**41.53**	**28.71**	**-12.82**
	7.4	*2.0*	*-4.1*	*3.4*	*2.0*	*-1.3*	*6.1*	*4.8*	*-1.4*
Q5 (high)	**44.17**	**3.63**	**-40.54**	**79.87**	**-6.87**	**-86.74**	**49.87**	**-18.13**	**-68.01**
	6.4	*0.4*	*-3.6*	*9.8*	*-0.7*	*-7.0*	*7.2*	*-2.7*	*-7.1*
Q5-Q1	**0.81**	**-7.05**		**59.89**	**-16.93**		**8.34**	**-46.85**	
	0.1	*-0.7*		*6.0*	*-1.6*		*0.9*	*-5.2*	
	Sorted by SIGMA			*Sorted by CVOL*			*Sorted by DISP*		
	Bad news	Good news	Good - bad	Bad news	Good news	Good - bad	Bad news	Good news	Good - bad
Q1 (low)	**35.48**	**42.60**	**7.12**	**49.54**	**27.81**	**-21.72**	**40.45**	**8.34**	**-32.10**
	4.6	*5.2*	*0.6*	*5.3*	*2.3*	*-1.4*	*5.8*	*1.3*	*-3.4*
Q5 (high)	**56.68**	**-40.92**	**-97.59**	**50.31**	**-18.65**	**-68.96**	**48.79**	**-12.63**	**-61.42**
	7.8	*-5.7*	*-9.6*	*6.2*	*-2.4*	*-6.1*	*5.7*	*-1.7*	*-5.5*
Q5-Q1	**21.19**	**-83.51**		**0.78**	**-46.46**		**8.34**	**-20.98**	
	2.0	*-7.7*		*0.1*	*-3.2*		*0.8*	*-2.2*	

Panel D: ρ^U estimated as median of ratios between delayed and immediate abnormal returns

	Sorted by 1/MV			*Sorted by 1/COV*			*Sorted by 1/AGE*		
Uncertainty	Bad news	Good news	Good - bad	Bad news	Good news	Good - bad	Bad news	Good news	Good - bad
Q1 (low)	**34.76**	**9.13**	**-25.63**	**18.31**	**9.40**	**-8.90**	**33.22**	**24.86**	**-8.36**
	12.4	*1.4*	*-6.8*	*6.5*	*1.3*	*-2.3*	*12.1*	*3.7*	*-2.2*
Q5 (high)	**39.36**	**2.14**	**-37.22**	**67.10**	**-7.04**	**-74.15**	**45.61**	**-11.50**	**-57.11**
	15.5	*0.3*	*-9.8*	*21.8*	*-1.0*	*-15.6*	*17.5*	*-1.7*	*-14.7*
Q5-Q1	**4.60**	**-6.99**		**48.80**	**-16.45**		**12.39**	**-36.35**	
	1.2	*-1.9*		*10.7*	*-4.1*		*3.1*	*-10.1*	
	Sorted by SIGMA			*Sorted by CVOL*			*Sorted by DISP*		
	Bad news	Good news	Good - bad	Bad news	Good news	Good - bad	Bad news	Good news	Good - bad
Q1 (low)	**31.53**	**34.82**	**3.29**	**35.65**	**30.49**	**-5.16**	**35.34**	**7.91**	**-27.43**
	11.9	*5.4*	*0.9*	*9.8*	*3.5*	*-1.1*	*10.7*	*1.0*	*-6.2*
Q5 (high)	**46.98**	**-26.75**	**-73.73**	**40.77**	**-13.79**	**-54.56**	**36.79**	**-9.78**	**-46.57**
	19.5	*-4.2*	*-20.5*	*12.4*	*-1.6*	*-11.1*	*12.6*	*-1.2*	*-10.6*
Q5-Q1	**15.46**	**-61.57**		**5.12**	**-44.28**		**1.45**	**-17.69**	
	4.1	*-18.1*		*1.0*	*-9.6*		*0.3*	*-4.3*	

Table A.5 - Stock price adjustment and earnings management
News: quarterly earnings releases

(percentage values; t statistics in italics)

The table refers to the post-earnings announcement drift (PEAD) data. The ρ^U measure the ratio between delayed and immediate abnormal stock returns; ρ^U=0 corresponds to immediate price adjustment, positive values to sluggish adjustment, negative values to price reversal. Stocks were divided into a ("high earnings management" group and a "low earnings management" group. The first comprises stocks for which the analysts' earnings forecast error (as a percentage of the lagged stock price) is between 0 and 0.001. The second includes all other stocks. The analysis of the four portfolios (good vs. bad news, high vs. low earnings management) was then performed as usual. The 0.001 threshold for the forecast error yields a number of observations equal to about one fourth of the total in the "high earnings management" group. Results are fairly insensitive to the choice of this threshold.

	Bad news	Good news	Good - bad
Earnings management is:	**Panel A: ρ^U estimated as ratio between delayed and immediate mean abnormal returns**		
Low	**32.85**	**30.89**	**-1.96**
	6.1	*6.3*	*-0.2*
High	**59.16**	**15.06**	**-44.10**
	8.8	*3.0*	*-3.9*
High-Low	**26.31**	**-15.83**	
	7.1	*-6.1*	
	Panel B: Share of stocks displaying price continuation		
Low	**58.11**	**52.58**	**-5.53**
	12.4	*3.9*	*-6.0*
High	**61.22**	**50.37**	**-10.84**
	15.2	*0.5*	*-10.3*
High-Low	**3.10**	**-2.21**	
	3.2	*-2.2*	
	Panel C: ρ^U estimated as ratio between delayed and immediate median abnormal returns		
Low	**61.09**	**21.42**	**-39.67**
	11.7	*4.3*	*-5.5*
High	**88.91**	**3.47**	**-85.44**
	14.7	*0.7*	*-10.7*
High-Low	**27.82**	**-17.95**	
	3.5	*-2.5*	
	Panel D: ρ^U estimated as median of ratios between delayed and immediate abnormal returns		
Low	**50.79**	**16.85**	**-33.94**
	46.0	*5.4*	*-21.6*
High	**74.13**	**4.55**	**-69.57**
	40.1	*1.3*	*-26.2*
High-Low	**23.33**	**-12.30**	
	10.6	*-5.7*	

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2007

S. SIVIERO and D. TERLIZZESE, *Macroeconomic forecasting: Debunking a few old wives' tales*, Journal of Business Cycle Measurement and Analysis , v. 3, 3, pp. 287-316, **TD No. 395 (February 2001).**

S. MAGRI, *Italian households' debt: The participation to the debt market and the size of the loan*, Empirical Economics, v. 33, 3, pp. 401-426, **TD No. 454 (October 2002).**

L. CASOLARO. and G. GOBBI, *Information technology and productivity changes in the banking industry,* Economic Notes, Vol. 36, 1, pp. 43-76, **TD No. 489 (March 2004).**

G. FERRERO, *Monetary policy, learning and the speed of convergence,* Journal of Economic Dynamics and Control, v. 31, 9, pp. 3006-3041, **TD No. 499 (June 2004).**

M. PAIELLA, *Does wealth affect consumption? Evidence for Italy*, Journal of Macroeconomics, Vol. 29, 1, pp. 189-205, **TD No. 510 (July 2004).**

F. LIPPI. and S. NERI, *Information variables for monetary policy in a small structural model of the euro area*, Journal of Monetary Economics, Vol. 54, 4, pp. 1256-1270, **TD No. 511 (July 2004).**

A. ANZUINI and A. LEVY, *Monetary policy shocks in the new EU members: A VAR approach,* Applied Economics, Vol. 39, 9, pp. 1147-1161, **TD No. 514 (July 2004).**

D. JR. MARCHETTI and F. Nucci, *Pricing behavior and the response of hours to productivity shocks,* Journal of Money Credit and Banking, v. 39, 7, pp. 1587-1611, **TD No. 524 (December 2004).**

R. BRONZINI, *FDI Inflows, agglomeration and host country firms' size: Evidence from Italy,* Regional Studies, Vol. 41, 7, pp. 963-978, **TD No. 526 (December 2004).**

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M. PAIELLA, *The foregone gains of incomplete portfolios,* Review of Financial Studies, Vol. 20, 5, pp. 1623-1646, **TD No. 625 (April 2007).**

K. BEHRENS, A. R. LAMORGESE, G.I.P. OTTAVIANO and T. TABUCHI, *Changes in transport and non transport costs: local vs. global impacts in a spatial network*, Regional Science and Urban Economics, Vol. 37, 6, pp. 625-648, **TD No. 628 (April 2007).**

M. BUGAMELLI, *Prezzi delle esportazioni, qualità dei prodotti e caratteristiche di impresa: analisi su un campione di imprese italiane,* v. 34, 3, pp. 71-103, Economia e Politica Industriale, **TD No. 634 (June 2007).**

G. ASCARI and T. ROPELE, *Optimal monetary policy under low trend inflation*, Journal of Monetary Economics, v. 54, 8, pp. 2568-2583, **TD No. 647 (November 2007).**

R. GIORDANO, S. MOMIGLIANO, S. NERI and R. PEROTTI, *The Effects of Fiscal Policy in Italy: Evidence from a VAR Model*, European Journal of Political Economy, Vol. 23, 3, pp. 707-733, **TD No. 656 (January 2008).**

B. ROFFIA and A. ZAGHINI, *Excess money growth and inflation dynamics*, International Finance, v. 10, 3, pp. 241-280, **TD No. 657 (January 2008).**

G. BARBIERI, P. CIPOLLONE and P. SESTITO, *Labour market for teachers: demographic characteristics and allocative mechanisms,* Giornale degli economisti e annali di economia, v. 66, 3, pp. 335-373, **TD No. 672 (June 2008).**

E. BREDA, R. CAPPARIELLO and R. ZIZZA, *Vertical specialisation in Europe: evidence from the import content of exports*, Rivista di politica economica, v. 97, 3, pp. 189, **TD No. 682 (August 2008).**

2008

P. ANGELINI, *Liquidity and announcement effects in the euro area*, Giornale degli Economisti e Annali di Economia, v. 67, 1, pp. 1-20, **TD No. 451 (October 2002).**

P. ANGELINI, P. DEL GIOVANE, S. SIVIERO and D. TERLIZZESE, *Monetary policy in a monetary union: What role for regional information?*, International Journal of Central Banking, v. 4, 3, pp. 1-28, **TD No. 457 (December 2002).**

F. SCHIVARDI and R. TORRINI, *Identifying the effects of firing restrictions through size-contingent Differences in regulation*, Labour Economics, v. 15, 3, pp. 482-511, **TD No. 504 (June 2004).**

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C. BIANCOTTI, G. D'ALESSIO and A. NERI, *Measurement errors in the Bank of Italy's survey of household income and wealth*, Review of Income and Wealth, v. 54, 3, pp. 466-493, **TD No. 520 (October 2004).**

S. MOMIGLIANO, J. HENRY and P. HERNÁNDEZ DE COS, *The impact of government budget on prices: Evidence from macroeconometric models*, Journal of Policy Modelling, v. 30, 1, pp. 123-143 **TD No. 523 (October 2004).**

L. GAMBACORTA, *How do banks set interest rates?*, European Economic Review, v. 52, 5, pp. 792-819, **TD No. 542 (February 2005).**

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R. FELICI and M. PAGNINI, *Distance, bank heterogeneity and entry in local banking markets*, The Journal of Industrial Economics, v. 56, 3, pp. 500-534, **No. 557 (June 2005).**

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M. PERICOLI and M. TABOGA, *Canonical term-structure models with observable factors and the dynamics of bond risk premia,* Journal of Money, Credit and Banking, v. 40, 7, pp. 1471-88, **TD No. 580 (February 2006).**

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F. BUSETTI and A. HARVEY, *Testing for trend*, Econometric Theory, v. 24, 1, pp. 72-87, **TD No. 614 (February 2007).**

V. CESTARI, P. DEL GIOVANE and C. ROSSI-ARNAUD, *Memory for prices and the Euro cash changeover: an analysis for cinema prices in Italy,* In P. Del Giovane e R. Sabbatini (eds.), The Euro Inflation and Consumers' Perceptions. Lessons from Italy, Berlin-Heidelberg, Springer, **TD No. 619 (February 2007).**

B. H. HALL, F. LOTTI and J. MAIRESSE, *Employment, innovation and productivity: evidence from Italian manufacturing microdata*, Industrial and Corporate Change, v. 17, 4, pp. 813-839, **TD No. 622 (April 2007).**

J. SOUSA and A. ZAGHINI, *Monetary policy shocks in the Euro Area and global liquidity spillovers,* International Journal of Finance and Economics, v.13, 3, pp. 205-218, **TD No. 629 (June 2007).**

M. DEL GATTO, GIANMARCO I. P. OTTAVIANO and M. PAGNINI, *Openness to trade and industry cost dispersion: Evidence from a panel of Italian firms,* Journal of Regional Science, v. 48, 1, pp. 97-129, **TD No. 635 (June 2007).**

P. DEL GIOVANE, S. FABIANI and R. SABBATINI, *What's behind "inflation perceptions"? A survey-based analysis of Italian consumers,* in P. Del Giovane e R. Sabbatini (eds.), *The Euro Inflation and Consumers' Perceptions. Lessons from Italy,* Berlin-Heidelberg, Springer, **TD No. 655 (January 2008).**

R. BRONZINI, G. DE BLASIO, G. PELLEGRINI and A. SCOGNAMIGLIO, *La valutazione del credito d'imposta per gli investimenti,* Rivista di politica economica, v. 98, 4, pp. 79-112, **TD No. 661 (April 2008).**

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A. SILVESTRINI and D. VEREDAS, *Temporal aggregation of univariate and multivariate time series models: a survey,* Journal of Economic Surveys, v. 22, 3, pp. 458-497, **TD No. 685 (August 2008).**

2009

F. PANETTA, F. SCHIVARDI and M. SHUM, *Do mergers improve information? Evidence from the loan market*, Journal of Money, Credit, and Banking, v. 41, 4, pp. 673-709, **TD No. 521 (October 2004).**

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M. PERICOLI and M. SBRACIA, *The CAPM and the risk appetite index: theoretical differences, empirical similarities, and implementation problems*, International Finance, v. 12, 2, pp. 123-150, **TD No. 586 (March 2006).**

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S. MAGRI, *The financing of small innovative firms: the Italian case*, Economics of Innovation and New Technology, v. 18, 2, pp. 181-204, **TD No. 640 (September 2007).**

S. MAGRI, *The financing of small entrepreneurs in Italy*, Annals of Finance, v. 5, 3-4, pp. 397-419, **TD No. 640 (September 2007).**

V. DI GIACINTO and G. MICUCCI, *The producer service sector in Italy: long-term growth and its local determinants*, Spatial Economic Analysis, Vol. 4, No. 4, pp. 391-425, **TD No. 643 (September 2007).**

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R. GOLINELLI and S. MOMIGLIANO, *The Cyclical Reaction of Fiscal Policies in the Euro Area. A Critical Survey of Empirical Research*, Fiscal Studies, v. 30, 1, pp. 39-72, **TD No. 654 (January 2008).**

P. DEL GIOVANE, S. FABIANI and R. SABBATINI, *What's behind "Inflation Perceptions"? A survey-based analysis of Italian consumers,* Giornale degli Economisti e Annali di Economia, v. 68, 1, pp. 25-52, **TD No. 655 (January 2008).**

F. MACCHERONI, M. MARINACCI, A. RUSTICHINI and M. TABOGA, *Portfolio selection with monotone mean-variance preferences,* Mathematical Finance, v. 19, 3, pp. 487-521, **TD No. 664 (April 2008).**

M. AFFINITO and M. PIAZZA, *What are borders made of? An analysis of barriers to European banking integration,* in P. Alessandrini, M. Fratianni and A. Zazzaro (eds.): The Changing Geography of Banking and Finance, Dordrecht Heidelberg London New York, Springer, **TD No. 666 (April 2008).**

G. FERRERO and A. NOBILI, *Futures contract rates as monetary policy forecasts,* International Journal of Central Banking, v. 5, 2, pp. 109-145, **TD No. 681 (June 2008).**

L. ARCIERO, C. BIANCOTTI, L. D'AURIZIO and C. IMPENNA, *Exploring agent-based methods for the analysis of payment systems: A crisis model for StarLogo TNG,* Journal of Artificial Societies and Social Simulation, v. 12, 1, **TD No. 686 (August 2008).**

A. CALZA and A. ZAGHINI, *Nonlinearities in the dynamics of the euro area demand for M1,* Macroeconomic Dynamics, v. 13, 1, pp. 1-19, **TD No. 690 (September 2008).**

L. FRANCESCO and A. SECCHI, *Technological change and the households' demand for currency,* Journal of Monetary Economics, v. 56, 2, pp. 222-230, **TD No. 697 (December 2008).**

G. ASCARI and T. ROPELE, *Trend inflation, taylor principle, and indeterminacy,* Journal of Money, Credit and Banking, v. 41, 8, pp. 1557-1584, **TD No. 708 (May 2007).**

S. COLAROSSI and A. ZAGHINI, *Gradualism, transparency and the improved operational framework: a look at overnight volatility transmission*, International Finance, v. 12, 2, pp. 151-170, **TD No. 710 (May 2009).**

M. BUGAMELLI, F. SCHIVARDI and R. ZIZZA, *The euro and firm restructuring*, in A. Alesina e F. Giavazzi (eds): Europe and the Euro, Chicago, University of Chicago Press, **TD No. 716 (June 2009).**

B. HALL, F. LOTTI and J. MAIRESSE, *Innovation and productivity in SMEs: empirical evidence for Italy,* Small Business Economics, v. 33, 1, pp. 13-33, **TD No. 718 (June 2009).**

2010

S. MAGRI, *Debt maturity choice of nonpublic Italian firms* , Journal of Money, Credit, and Banking, v.42, 2-3, pp. 443-463, **TD No. 574 (January 2006).**

E. IOSSA and G. PALUMBO, *Over-optimism and lender liability in the consumer credit market,* Oxford Economic Papers, v. 62, 2, pp. 374-394, **TD No. 598 (September 2006).**

S. NERI and A. NOBILI, *The transmission of US monetary policy to the euro area,* International Finance, v. 13, 1, pp. 55-78, **TD No. 606 (December 2006).**

M. IACOVIELLO and S. NERI, *Housing market spillovers: evidence from an estimated DSGE model,* American Economic Journal: Macroeconomics, v. 2, 2, pp. 125-164, **TD No. 659 (January 2008).**

A. ACCETTURO, *Agglomeration and growth: the effects of commuting costs*, Papers in Regional Science, v. 89, 1, pp. 173-190, **TD No. 688 (September 2008).**

A. B. ATKINSON and A. BRANDOLINI, *On analysing the world distribution of income*, World Bank Economic Review , v. 24, 1 , pp. 1-37, **TD No. 701 (January 2009).**

R. CAPPARIELLO and R. ZIZZA, *Dropping the Books and Working Off the Books,* Labour, v. 24, 2, pp. 139-162 ,**TD No. 702 (January 2009).**

F. COLUMBA, L. GAMBACORTA and P. E. MISTRULLI, *Mutual Guarantee institutions and small business finance,* Journal of Financial Stability, v. 6, 1, pp. 45-54, **TD No. 735 (November 2009).**

A. BRANDOLINI, S. MAGRI and T. M SMEEDING, *Asset-based measurement of poverty*, Journal of Policy Analysis and Management, v. 29, 2 , pp. 267-284, **TD No. 755 (March 2010).**

FORTHCOMING

L. MONTEFORTE and S. SIVIERO, *The Economic Consequences of Euro Area Modelling Shortcuts,* Applied Economics, **TD No. 458 (December 2002).**

M. BUGAMELLI and A. ROSOLIA, *Produttività e concorrenza estera*, Rivista di politica economica, **TD No. 578 (February 2006).**

G. DE BLASIO and G. NUZZO, *Historical traditions of civicness and local economic development*, Journal of Regional Science, **TD No. 591 (May 2006).**

R. BRONZINI and P. PISELLI, *Determinants of long-run regional productivity with geographical spillovers: the role of R&D, human capital and public infrastructure,* Regional Science and Urban Economics, **TD No. 597 (September 2006).**

G. FERRERO, A. NOBILI and P. PASSIGLIA, *Assessing Excess Liquidity in the Euro Area: The Role of Sectoral Distribution of Money,* Applied Economics, **TD No. 627 (April 2007).**

A. CIARLONE, P. PISELLI and G. TREBESCHI, *Emerging Markets' Spreads and Global Financial Conditions,* Journal of International Financial Markets, Institutions & Money, **TD No. 637 (June 2007).**

Y. ALTUNBAS, L. GAMBACORTA and D. MARQUÉS, *Securitisation and the bank lending channel*, European Economic Review, **TD No. 653 (November 2007).**

F. BALASSONE, F. MAURA and S. ZOTTERI, *Cyclical asymmetry in fiscal variables in the EU*, Empirica, **TD No. 671 (June 2008).**

M. BUGAMELLI and F. PATERNÒ, *Output growth volatility and remittances*, Economica, **TD No. 673 (June 2008).**

F. D'AMURI, O. GIANMARCO I.P. and P. GIOVANNI, *The labor market impact of immigration on the western german labor market in the 1990s,* European Economic Review, **TD No. 687 (August 2008).**

L. FORNI, A. GERALI and M. PISANI, *Macroeconomic effects of greater competition in the service sector: the case of Italy,* Macroeconomic Dynamics, **TD No. 706 (March 2009).**

Y. ALTUNBAS, L. GAMBACORTA, and D. MARQUÉS-IBÁÑEZ, *Bank risk and monetary policy,* Journal of Financial Stability, **TD No. 712 (May 2009).**

V. DI GIACINTO, G. MICUCCI and P. MONTANARO, *Dynamic macroeconomic effects of public capital: evidence from regional Italian data,* Giornale degli economisti e annali di economia, **TD No. 733 (November 2009).**

A. GERALI, S. NERI, L. SESSA and F. M. SIGNORETTI, *Credit and banking in a DSGE model of the Euro Area,* Journal of Money, Credit and Banking, **TD No. 740 (January 2010).**

L. FORNI, A. GERALI and M. PISANI, *The macroeconomics of fiscal consolidations in euro area countries,* Journal of Economic Dynamics and Control, **TD No. 747 (March 2010).**