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Accuracy of European Stock Target Prices †

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† The views and opinions expressed in this paper are not necessarily those of KPMG. This study was developed for academic purposes only.

Abstract: Equity studies are conducted by professionals, who also provide buy/hold/sell recommendations to investors. Nowadays, target prices determined by financial analysts are publicly available to investors, who may decide to use them for investment purposes. Studying the *accuracy* of such analysts' forecasts is, thus, of paramount importance. Based upon empirical data on 50 of the biggest (larger capitalisation) European stocks over a 15-year period, from 2004 to 2019, and using a panel data approach, this is the first study looking at overall accuracy in European stock markets. We find that *Bloomberg's 12-month consensus target prices* have no predictive power over future market prices. Our panel results are robust to company fixed effects and subperiod analysis. These results are in line with the (mostly US-based) evidence in the literature. Extending common practice, we perform a comparative accuracy analysis, comparing the accuracy of target prices with that of simple capitalisations of current prices. It turns out target prices are not better at forecasting than simple capitalisations. When considering individual regressions, accuracy is still very low, but it varies considerably across stocks. By also analysing the relationship between both measures—target prices and capitalised prices—we find evidence that, for some stocks, capitalised prices partially explain how target prices are determined.

Keywords: target prices; forecast accuracy; panel data analysis

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1. Introduction

Currently, millions of shares are traded daily on world markets. Investors who buy and sell shares wonder if they are trading at the right/fair prices.

Defenders of market efficiency would claim market prices are "fair" by definition and that there is no added value to stock picking. Still, financial markets are full of financial analysts that keep analysing stocks and providing buy/hold/sell recommendations, suggesting it is possible to "beat" the market by investing according to their advice. These analyses typically also provide so-called "price targets". According to Bilinski et al. (2013), "a target price forecast reflects the analyst's estimate of the firm's stock price level in 12 months, providing easy to interpret, direct investment advice".

Nowadays, price targets determined by financial analysts are available to investors via platforms such as Bloomberg or even Yahoo Finance and can, therefore, be used for defining investment strategies. Although price targets may vary from analyst to analyst, depending on the models they use and parameter estimations, one can rely on overall statistics, also provided by financial data platforms.

In this study, we use *Bloomberg's 12-month consensus target prices* for 50 of the highest capitalisation European stocks, over the past 15 years, and look into their predictive power. This statistic is calculated by Bloomberg taking the estimates of all analysts who are, at a given moment, publishing 12-month ahead estimates for a company and averaging these numbers out. We use panel regressions to study analysts' target price accuracy for the

European stock market. In addition to Bonini et al. (2010), which focuses on Italian stocks alone, this is the first study providing European evidence on target price accuracy. Our results are in line with the (mostly US-based) literature, suggesting that globally average prices targets have no predictive power.

In addition, we propose our own 12-month forecast statistic based on simple capitalisation of current prices. This kind of *comparative accuracy* analysis is very informative and new in the literature. Unquestionably naive, our forecast measure proves to have the same level of (non-)accuracy of analysts' target prices, suggesting both forecasts are equally (non-)reliable. Although globally it slightly outperforms target prices, the differences are too small to be statistically meaningful. By also studying the relationship between both forecasts, in terms of informativeness, we conclude that target prices and capitalised prices contain different types of information, as at least globally they prove to be uncorrelated.

The full sample findings are robust and consider the firm-specific fixed effects and subperiod analysis. Concretely, we look at three subperiods: the pre-crisis period (until the end of August 2008), crisis (between September 2008 and end of 2012) and post-crisis period (from 2013 onwards). Despite the consistently bad accuracy of target prices, no matter the subperiod, we do find analysts were pessimistic before and during the crisis, contradicting the full-sample results where we attest to their overall optimism. These optimism/pessimism results are in line with the previous literature—see (Bradshaw et al. 2014; Bradshaw et al. 2016; Engelberg et al. 2020).

The remainder of the text is organised as follows. Section 2 presents a brief literature overview. Section 3 describes the data and research design. Section 4 presents and discusses the results. Finally, Section 5 summarises the main findings and discuss possible limitations of our approach.

2. Literature Overview

The discussion about whether or not price targets can be used to "beat" the market is related to the much older but ongoing debate about passive vs. active portfolio management, or even to the more general discussion about the market efficiency—see (Fama 1965; Fama et al. 1969; Barr Rosenberg and Lanstein 1984; Sharpe 1991; Admati and Pfleiderer 1997; Sorensen et al. 1998; Malkiel 2003; Shukla 2004; French 2008; Vermorken et al. 2013; Cao et al. 2017; Elton et al. 2019), to mention just a few.

Although the literature about market efficiency presents mixed evidence, depending on concrete markets, asset classes and/or forms of efficiency under analysis (see Dimson and Mussavian 1998 overview), there seems to be an agreement that, in particular for large capitalisation stocks, markets are supposed to be at least semi-strong efficient. That is, one should not be able to trade profitably on the basis of publicly available information, such as analysts' recommendations and target prices. Nonetheless, research departments of brokerage houses spend large sums of money on security analysis —with particular emphasis on large capitalisation stocks—presumably because these firms and their clients believe its use can generate superior returns (Barber et al. 2001), suggesting markets may not be that efficient.

In addition to the non-efficiency argument, it could also be that target prices act in financial markets as self-fulfilling prophecies. See, for instance, the early and recent overviews in Krishna (1971) and Zulaika (2019), respectively. A self-fulfilling prophecy is an event that is caused only by the preceding prediction or expectation that it was going to occur. If extremely large numbers of people base trading decisions on the same indicators, thereby using the same information to take their positions, this in turn pushes the price in the predicted direction. The self-fulfilling prophecy argument has been mostly used in studies about financial bubbles (Garber 1989), market cycles (Farmer Roger 1999) or panics (Calomiris and Mason 1997), but also to justify some industry (theoretically odd) trading practices, such as technical analysis (Menkhoff 1997; Oberlechner 2001; Reitz 2006) and momentum (Jordan 2014), for instance. Most analysts determining price targets work at high status entities such as consulting firms and investment banks. It turns out that the reputation of these entities ultimately could significantly influence the behaviour of investors, in our view, supporting the self-fulling argument.

Early investigations on the market impact of analysts are primarily related to the market's reaction to revisions in either analysts' earnings forecasts or recommendations. For example, Abdel-Khalik and Ajinkya (1982) find significant abnormal returns during the publication week of forecast revisions by Merrill Lynch analysts. Similarly, the authors of Lys and Sohn (1990) present evidence consistent with forecast revisions (see also Stickel 1991).

Later studies on target prices' informativeness examine their predictability either in the short term or the long term. While they unanimously document a significant short-term market reaction to the release of target prices (Asquith et al. 2005; Bradshaw et al. 2013; Brav and Lehavy 2003), many find little evidence of target prices' long-term predictability (Bonini et al. 2010; Bradshaw et al. 2013; Da and Schaumburg 2011). Indeed, the authors of Bonini et al. (2010) find that analysts' forecasting ability of target prices is limited. Additionally, Bradshaw et al. (2013) finds no evidence of persistence in forecasting accuracy of target prices. On the contrary, covering data from 16 countries, Bilinski et al. (2013) provides evidence that analysts have differential and persistent skill to issue accurate target price forecasts.

More recent studies on target price focus either on the determinants of target prices (Da et al. 2016) or on exploring the possible relationship between their accuracy and a variety of analysts, markets, accounting systems (Bradshaw et al. 2019), firm or governance (Cheng et al. 2019) characteristics among others, happily ignoring the fact most evidence points to very low accuracy levels.

In this study, we go back to *accuracy evaluation*, providing empirical evidence on the virtually unexplored European stock market.

3. Data and Methodology

3.1. Data

This study focuses on 50 major (high capitalisation) European companies' stocks. From all the constituents of EURO STOXX 50 index during the 15 years under analysis, we chose the 50 companies that *stayed the longest* in the index. These companies are listed in Table 1.

Table 1. List of European stocks under analysis (by alphabetic order).

Adidas	BASF	E.ON	L'Oreal	Schneider Electric SE
Air Liquide	Bayer	ENEL	LVMH	Siemens
Airbus	BNP Paribas	ENI	Mucich RE	Societe Generale
Allianz	BMW	Essilor	Nokia	Telefonica
Anheuser	Danone	Fresenius	Orange	Total
ASML	Carrefour	Iberdrola	Repsol	Unicredit
Assicurazioni	Daimler	Inditex	Safran	Unilever
AXA Deutsche	Bank	ING	Saint-Gobain	Vinci
Banco Bilbao	Deutsche Post	Intesa Sanpaolo	Sanofi	Vivendi
Banco Santander	Deutsche Telekom	Philips	SAP	Volkswagen

From Table 1, it is clear that we do not focus on any particular country or sector, as the listed companies belong to variety of countries and all sort of sectors, such as air freight and logistics; airspace and defense; automobile manufacturers; chemicals; construction and engineering; consumer durables and apparel; diversified chemicals; diversified banks; electric components and equipment; electric utilities; food products; food, beverage and tobacco; health care equipment; industrial conglomerates; integrated oil and gas; integrated telecommunication services; movies and entertainment; multi-line insurance; personal products; pharmaceuticals; real estate; reinsurance; retailing; semiconductors, software; technology hardware and equipment; and hypermarkets, supermarkets, convenience stores, cash and carry, e-commerce.

For each of the companies under analysis, we collected weekly (close) prices and the so-called *Bloomberg's 12-month consensus target prices* , from 27 April 2004 to 23 April 2019, providing us with a total of 78,300 observations.

Our accuracy analysis is based upon three variables: observed futures prices (FP), 12-month ahead target prices (TP) forecasts on FP and capitalised prices (CP) forecasts for the same FP based upon market prices one year before.

Definition 1. *We denote by FP_{it} the future price (FP) of company i observed at the future date t. TP_{it} is the 12-month target price for date t, observed one year in advance, i.e., at $t-52$, weekly observed data. CP_{it} is the capitalised price of company i for date t, determined as*

$$CP_{it} = P_{i,t-52} \times e^{\bar{R}_i \times 52} \tag{1}$$

where $P_{i,t-52}$ is the market price of company i observed one year in advance at date $t-52$ and $\bar{R}$ is the weekly average past return of company i.

Using the above definition, TP_t and CP_t are one-year ahead forecasts for FP_t.

3.2. Research Design

Our predictive power analysis relies mostly on panel data regressions.

The idea is to analyse to what extent analysts' target prices (TP) forecast futures prices (FP) and compare their forecasting performance to that of using simple capitalisations of current market prices—capitalised prices (CP). By also regressing target prices on the mentioned capitalised prices, one can also get an idea about how much target prices actually result from simple capitalisation rules.

Thus, we look into three types of pairwise relationships:

(A) FP vs. TP: we evaluate the accuracy of TP forecasts made by analysts.
(B) FP vs. CP: to compare the accuracy of a forecast as naive as CP to analysts' TP forecast.
(C) TP vs. CP: to evaluate to what extent TP can be determined by CP.

The basic linear panel models used in econometrics can be described through suitable restrictions of the following general model:

$$y_{it} = \alpha_{it} + \beta_{it} x_{it} + u_{it} \tag{2}$$

where a u_{it} represents a random disturbance term of mean 0.

In our case, y_{it} is either FP_{it} (in (A) and (B) listed above) or TP_{it} (for (C)) and x_{it} is either TP_{it} (in (A)) or CP_{it} (in (B) and (C)), with FP_{it}, TP_{it} and CP_{it} as in the variables Definition 1, whenever we are considering *in level* panel regressions. For *in difference* panel regressions, we consider its differences $\Delta FP_{it} = FP_{it} - FP_{i,t-1}$, $\Delta TP_{it} = TP_{it} - TP_{i,t-1}$, and $\Delta CP_{it} = CP_{it} - CP_{i,t-1}$ accordingly.

Table 2 shows that our *panel variables*—FP, TP and CP—are non-stationary, but are integrated in the order of one[1].

Therefore, when regressing our level panel variables on one another, one needs to be very careful with interpretations, as mostly there is likely nothing but spurious relationships. For further discussion on spurious relationship identification, see, for instance Granger and Newbold (2001). Despite this, intercept coefficients of *in level panel regressions* can be interpreted as optimism/pessimism indicators (forecast bias), when we use target prices as predictors of future prices. Likewise, when capitalised prices are used to predict future prices, intercept levels can be interpreted in terms of how much past returns over or under estimate future returns.

Table 2. Panel unit root test results.

	Future Prices (FP)		Target Prices (TP)		Capitalised Prices (CP)	
Method	**Statistic**	**Prob**	**Statistic**	**Prob**	**Statistic**	**Prob**
LLC	6.755	1.000	7.966	1.000	7.074	1.000
IPS	6.156	1.000	8.492	1.000	6.635	1.000
ADF– Fisher	60.653	0.999	39.983	0.999	53.817	1.000
PP–Fisher	57.242	1.000	40.002	1.000	49.630	1.000

Results of the LLC (Levin et al. 2002), the null hyphothesis of which assumes common unit root process, and IPS (Im, Pesaran, and Shin 2003), Fisher-type (Choi 2001) tests that as the null hypothesis assume an individual unit root process, considering a cross-section of 50 time series, individual effects, such as exogenous variables, and automatic maximum lags and lag length selection based on SIC (Schwarz et al. 1978). Probabilities for Fisher tests are computed using the asymptotic Chi-square distribution. All other tests assume asymptotic normality.

On the other hand, accuracy can only be properly evaluated from *in differences panel regressions*. For completeness, in Section 4 (or in the Appendix A), we present regression results both on levels and differences.

3.2.1. Overall Panel Regressions

We start by considering parameter homogeneity, i.e., $\alpha_{it} = \alpha$ and $\beta_{it} = \beta$ for all i, t. The resulting model

$$y_{it} = \alpha + \beta x_{it} + u_{it} \tag{3}$$

is a standard linear model pooling all the data across i and t.

This is the most common panel model and by considering fixed parameters, we aim to evaluate the overall relationship between y and x. Then, we consider two less restrictive models: cross-fixed effects models and period fixed effect models.

3.2.2. Panel Robustness

We checked the robustness of the overall panel regression results in two ways: by considering individual company fixed effects and by performing subperiod panel regressions.

To model individual company heterogeneity, we assume that the error term in (3) has two separate components,

$$u_{it} = \mu_i + \epsilon_{it} \tag{4}$$

μ_i is firm-specific and does not change over time, and ϵ_{it} is a random disturbance term of mean 0.

By replacing (4) in the general Equation (3), we obtain

$$y_{it} = \alpha + \beta x_{it} + \mu_i + \epsilon_{it}. \tag{5}$$

As in our case, it is likely that if the individual component is correlated with the regressors, the ordinary least squares (OLS) estimator of β would be inconsistent, so it is customary to treat the μ_i as a further set of n parameters to be estimated, as if in the general model $\alpha_{it} = \alpha_i = \alpha + \mu_i$ for all t.

In panel data terminology, μ_i are called *fixed effects* (otherwise known as within or least squares dummy variables) model, estimated by OLS on transformed data, guaranteeing consistent estimates for β.

To test the robustness of our panel results over time, instead of considering time-fixed effects, we opted to take a different perspective, estimating additional panel regressions (as in (3)), for three subperiods:

- The *pre-crisis period*, until the end of August 2008;
- The *crisis period*, from September 2008 until the end of 2012;
- The *pots crisis period*, from 2013 onwards.

These are well-established subperiods for European stock markets[2]. When compared to a more formal structural break analysis, as proposed for instance in Okui and Wang (2021), considering these concrete sub-periods has the advantage of interpretability and comparability vis a vis the already vast literature around the financial crisis.

3.2.3. Individual Regressions

Finally, we also consider individual regressions, which is the same as allowing both coefficients α_i and β_i to vary for each firm i,

$$y_{it} = \alpha_i + \beta_i x_{it} + u_{it}. \tag{6}$$

For illustration purposes, Figure 1 shows the evolution of the three variables—future prices (FP), target prices (TP) and capitalised prices (CP)—for the eight best performing companies over the 15-year period of our sample.

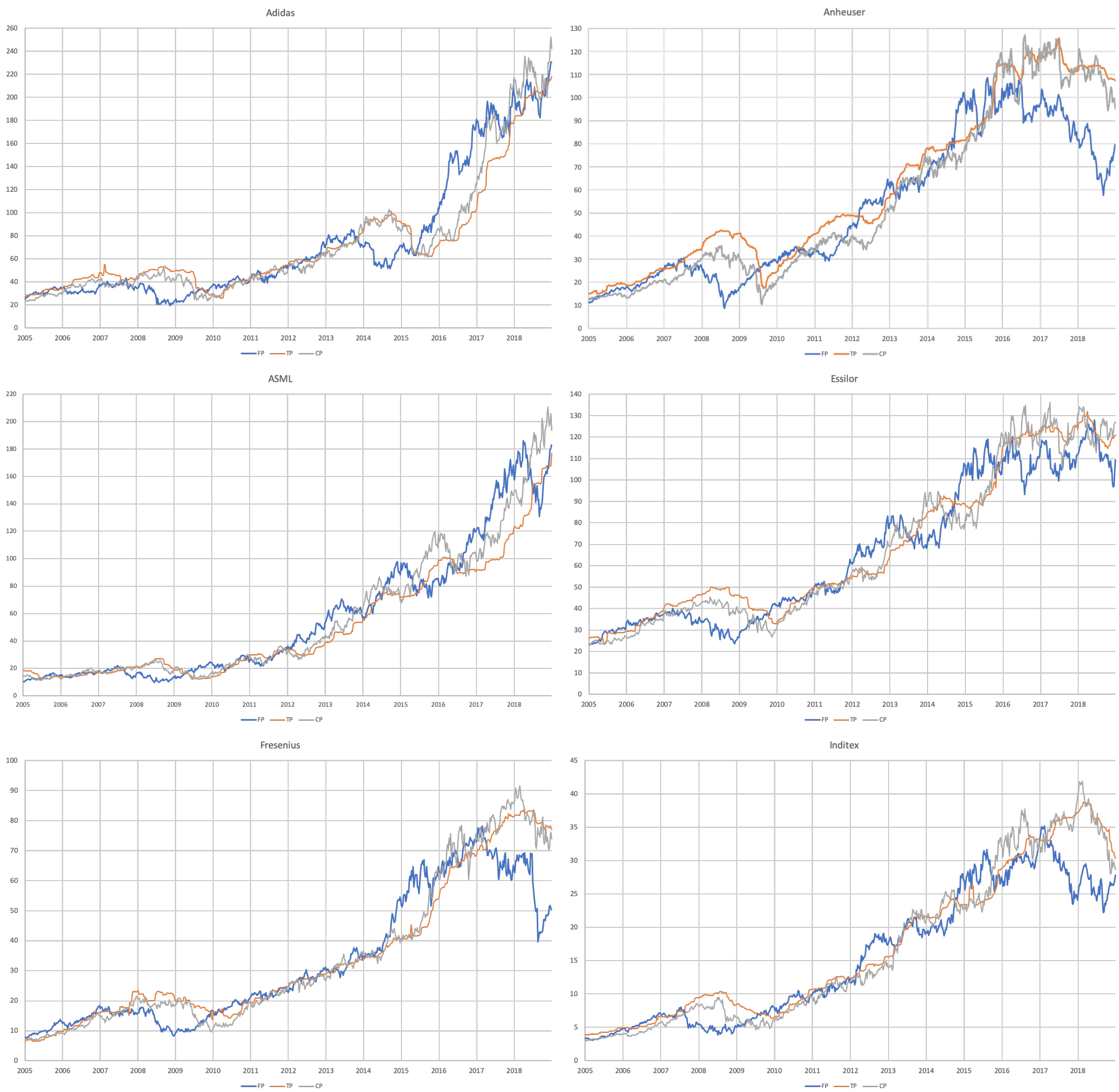

Figure 1. *Cont.*

Figure 1. Comparison of target prices (TP) and capitalised prices (CP) with actual future prices (FP). Target prices (TP: orange lines) and capitalised prices (CP: grey lines) forecast *for* the indicated date *t*, jointly with actually observed future prices (FP: blue lines) *at t*, for the 8 best performing companies over the 15-year period of our sample: Adidas, Anheuser, ASML, Essilor, Fresenius, Inditex, Safran, Volkswagen.

4. Results

4.1. Overall Panel Regressions

Table 3 summarises the overall panel regression results (Figure 2 illustrates them). As previously discussed, level regressions should be interpreted with extreme care, as we are dealing with non-stationary variables (recall results in Table 2). These relationships are indeed spurious as confirmed by the extremely small Durbin–Watson statistic values in Table 3 (0.019, 0.047 and 0.037)[3]. In practical terms, this means that, based upon level regressions, we cannot infer the relationship between the dependent and independent variables—we cannot interpret dependent variables coefficients nor use regression statistics to attest models quality. Still, we can interpret the constant coefficient and its significance.

From level results columns—(1), (3) and (5) in Table 3—we show evidence that:

- In our overall sample and on average, target prices overestimate future prices (positive and statistically significant negative $\alpha = -1.424$);
- While capitalised prices tend to under estimate them (positive and statistically significant positive $\alpha = +1.789$).

This is in line with the literature attesting that the majority of target prices are too optimistic, supporting theoretical predictions by Ottaviani and Sørensen (2006), in line with the results of Bonini et al. (2010).

In terms of forecast accuracy, what can be interpreted are the results for the regressions in differences. From the analysis of the in difference results—columns (2), (4) and (6) in Table 3—we can conclude that:

- Overall, there is no evidence that target prices can forecast future prices—the second column of results in Table 3. In fact, the regression not only shows and R^2 of 0.000, but also the coefficient associated with the independent variable is also not statistically different from zero (as attested by its t-statistics);
- Although is true we also find no forecasting power in the simple capitalisation rule forecasts (from Equation (1))—the fourth column of results in Table 3—as we observe an R^2 of 0.001, in this case the coefficient associated with the dependent variable is at least statistically different from zero;
- The ability capitalised prices have to explain analysts' forecasts is very limited—sixth column of results in Table 3. In fact, we only get an $R^2 = 0.008$. Nonetheless, in relative terms this regression is the "best", as attested by the all model selection statistics.

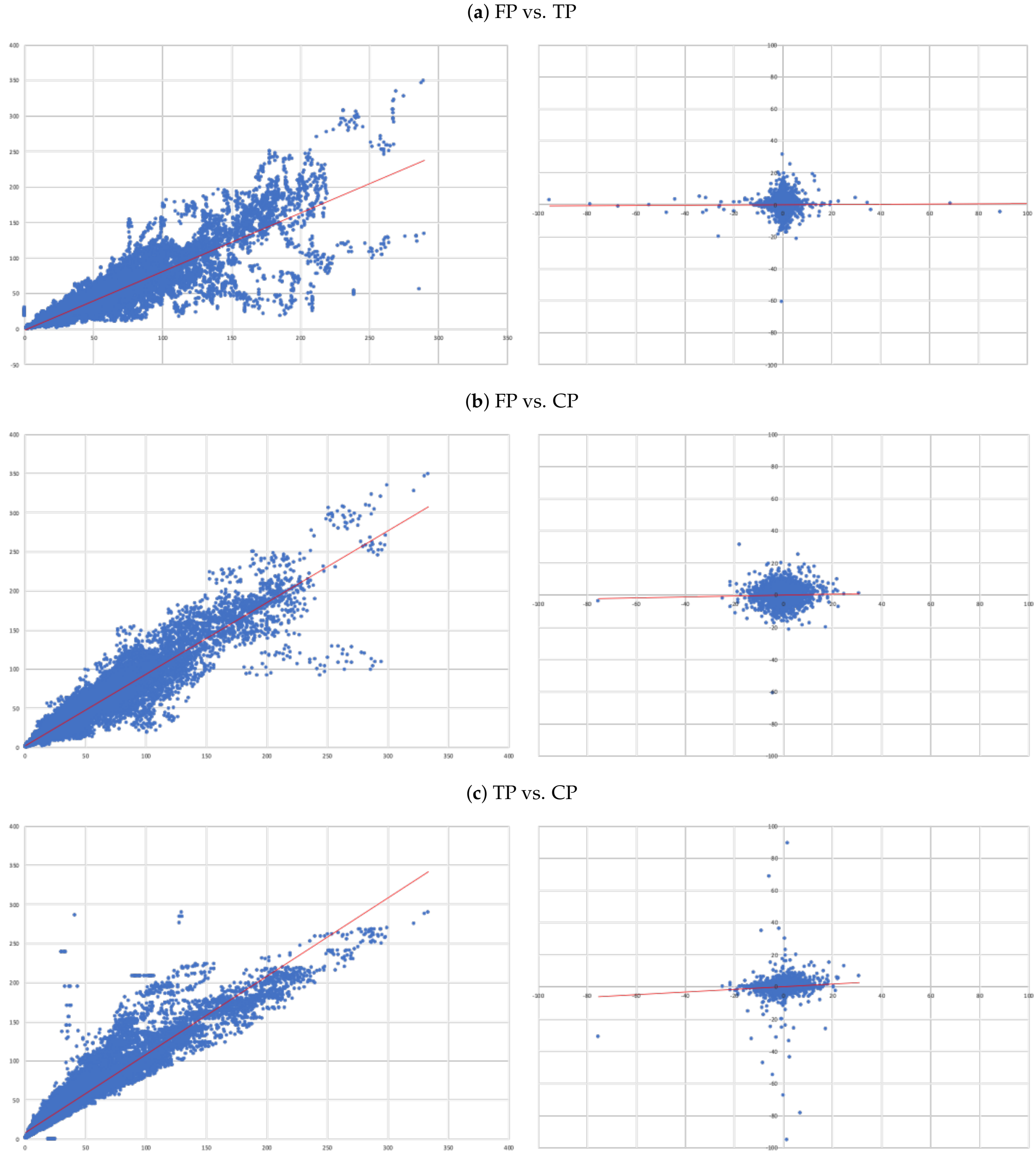

Figure 2. Panel regressions' illustration. Illustration of the panel regressions of Table 3. On the left-hand-side are images of level regressions and on the right-hand–ide are regressions in differences.

Table 3. Overall panel regressions.

	FP vs. TP		FP vs. CP		TP vs. CP	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Dependent Variable	FP	ΔFP	FP	ΔFP	TP	ΔTP
Mean dependent var	38.516	0.070	38.516	0.070	48.456	0.057
S.D. Dependent var	39.241	1.839	39.241	1.839	42.886	1.758
Intercept						
Coefficient	−1.424	0.069	1.789	0.068	8.433	0.051
Std. Error	0.134	0.010	0.085	0.010	0.096	0.009
t-Statistic	−10.590	7.192	20.922	7.012	87.712	5.525
Prob.	0.000	0.000	0.000	0.000	0.000	0.000
Independent Variable	TP	ΔTP	CP	ΔCP	CP	ΔCP
Coefficient	0.824	0.007	0.916	0.029	0.999	0.081
Std. Error	0.002	0.005	0.001	0.005	0.002	0.004
t-Statistic	396.586	1.215	613.740	5.851	594.747	17.470
Prob.	0.000	0.224	0.000	0.000	0.000	0.000
Regression Statistics						
R-squared	0.811	0.000	0.912	0.001	0.906	0.008
Adjusted R-squared	0.811	0.000	0.912	0.001	0.906	0.008
S.E. of regression	17.040	1.839	11.670	1.838	13.124	1.750
Sum square resid	106.123	123,419.8	4,977,847	123,309	6,295,006	111,838
Log Likelihood	−155,501	−740,255	−141,667	−74,009	−145,957	−72,226
F-statistic	157,281	1.476	376,676	34.241	353,724	305.203
Prob (F-statistic)	0.000	0.224	0.000	0.000	0.000	0.000
Model Statistics						
AIC	8.509	4.056	7.752	4.055	7.987	3.958
SIC	8.509	4.057	7.753	4.056	7.987	3.958
HQC	8.509	4.056	7.752	4.056	7.987	3.958
Residuals Autocorr.						
Durbi–Watson stat	0.019	2.055	0.047	2.055	0.037	2.007

Regression results using panel least squares based upon 36,550 balanced panel observations (with a total of 731 periods included and 50 cross-sections). Panel variables are future prices (FP), target prices (TP) and capitalised prices (CP). Each column represents a specific panel regression as in Equation (3). We regress FP on TP, FP on CP and TP on CP, both in levels and differences. We report the model selection criteria of Akaike (1973) (AIC), (Schwarz et al. 1978) (SIC) and Hannan and Quinn (1979) (HQC). For residual autocorrelation we use the panel data generalisation by Bhargava et al. (1982) of the classical Durbin and Watson (1950) statistic.

4.2. Panel Robustness

Considering company fixed effects does not considerably change the "picture" in terms of accuracy (see in difference columns (2), (4) and (6) of Table A1, in the Appendix A), it seems that:

- The reason why, overall, our forecast variables (both TP and CP) have no predicting power over future prices cannot be explained by firm-specific components.

As before in the level regressions (columns (2), (4) and (6) of Table A1, in the Appendix A) are spurious. However, looking deeper into the variation of firm-specific estimates (μ_i in Equation (4), illustrated at Figure 3), it seems we can conclude:

- Firm-specific variables may explain optimism/pessimism in target prices forecasts, as we obtained a wide range of μ_i values.

Results also do no change much, when considering panel regressions over the three proposed subperiods: pre-crisis, crisis and post-crisis. Table 4 summarises the relevant statistics on the subperiod panel regressions (see full results for each of the subperiods in Tables A2–A4, in the Appendix A).

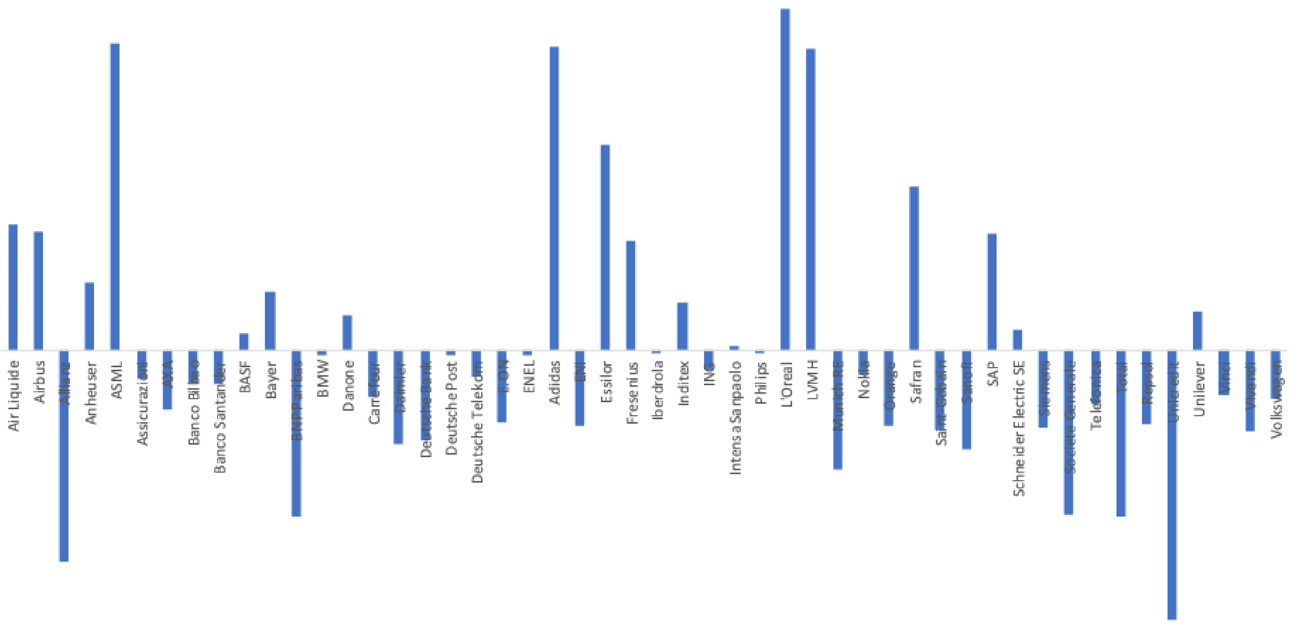

Figure 3. Company fixed effects.

Table 4. Summary of subperiod panel regression results.

	Pre-crisis	Crisis	Post-crisis
Panel A: FP vs. TP			
In level (1)			
Intercept	3.15669 ***	5.467543 ***	−1.025766 ***
In Differences (2)			
Intercept	0.036918 ***	0.038144 **	0.097836 ***
Independent Variable	0.016726 **	0.000336	0.086016 ***
Adjusted R-squared	0.000485	0.000089	0.001118
Hannan-Quinn criter.	3.19534	3.755410	4.451777
Panel B: FP vs. CP			
	Pre-crisis	Crisis	Post-crisis
In level (3)			
Intercept	2.219831 ***	2.480338 ***	2.701088 ***
In Differences (4)			
Intercept	0.027395 **	0.038147 **	0.102555 ***
Independent Variable	0.089025 ***	0.000953	0.032768 ***
Adjusted R-squared	0.004987	0.000088	0.001179
Hannan-Quinn criter.	3.190830	3.755	4.451717

Significative at 10% (*) 5% (**) or 1% (***).

Looking across periods its seems:

- Analysts became particularly pessimistic during the crisis-period (positive and significant $\alpha = 5.4675$ crisis period level intercept) and optimistic in the post-crisis period (negative and significant $\alpha = -1.02577$ for the equivalent post-crisis intercept);
- Absence of accuracy, of both target prices and capitalised prices, became even more severe during the crisis period (lowest adjusted R^2).

4.3. Individual Regressions

Perhaps most interesting are the individual sample results. Tables 5–7 show individual time series regressions for the eight best performing companies (the ones in Figure 1).

Table 5. Future prices vs. target prices: individual asset results. Individual regressions of future prices (FP) on target prices (TP): (**a**) in levels $FP_t = \alpha + \beta TP_t + \epsilon_t$ and (**b**) in differences $\Delta FP_t = \alpha + \beta \Delta TP_t + \epsilon_t$.

(**a**) In levels

	Adidas	Anheuser	ASML	Essilor	Fresenius	Inditex	Safran	Volkswagen
Regression Statistics								
Multiple R	0.9132	0.9245	0.9566	0.9489	0.9143	0.9391	0.9584	0.5404
R Square	0.8339	0.8547	0.9151	0.9004	0.8359	0.8818	0.9185	0.2921
Adjusted R Square	0.8336	0.8545	0.9150	0.9003	0.8357	0.8817	0.9184	0.2910
Standard Error	23.0141	11.6967	14.1228	10.2800	8.7074	3.3725	8.6591	41.2734
Observations	731	731	731	731	731	731	731	679
Intercept								
Coefficient	−6.5788	3.2317	−1.3111	2.7221	3.6783	1.2282	−7.0116	46.9403
Standard Error	1.5922	0.8641	0.8400	0.8709	0.5775	0.2310	0.5916	4.2281
t Stat	−4.1318	3.7398	−1.5608	3.1255	6.3691	5.3175	−11.8514	11.1019
P-value	0.0000	0.0002	0.1190	0.0018	0.0000	0.0000	0.0000	0.0000
Lower 95%	−9.7048	1.5352	−2.9602	1.0123	2.5445	0.7748	−8.1731	38.6385
Upper 95%	−3.4529	4.9283	0.3381	4.4319	4.8121	1.6817	−5.8501	55.2421
TP Variable								
Coefficient	1.1167	0.8049	1.1506	0.9225	0.8532	0.8437	1.2215	0.4511
Standard Error	0.0185	0.0123	0.0130	0.0114	0.0140	0.0114	0.0135	0.0270
t Stat	60.4917	65.4910	88.6353	81.1974	60.9478	73.7592	90.6476	16.7120
P-value	0.0000	0.0001	0.0002	0.0003	0.0004	0.0005	0.0006	0.0007
Lower 95%	1.0805	0.7808	1.1251	0.9002	0.8257	0.8212	1.1950	0.3981
Upper 95%	1.1530	0.8290	1.1761	0.9448	0.8807	0.8661	1.2480	0.5041
ANOVA								
SS	1,938,122	586,797	1,566,947	696,737	281,640	61,878	616,104	475,771
MS	1,938,122	586,797	1,566,947	696,737	281,640	61,878	616,104	475,771
F	3659	4289	7856	6593	3715	5440	8217	279
Significance F	0.0000	0.0001	0.0002	0.0003	0.0004	0.0005	0.0006	0.0007

(**b**) In differences

	Adidas	Anheuser	ASML	Essilor	Fresenius	Inditex	Safran	Volkswagen
Regression Statistics								
Multiple R	0.0124	0.0812	0.0297	0.0345	0.0137	0.0012	0.1157	0.0488
R Square	0.0002	0.0066	0.0009	0.0012	0.0002	0,0000	0.0134	0.0024
Adjusted R Square	−0.0012	0.0052	−0.0005	−0.0002	−0.0012	−0.0014	0.0120	0.0002
Standard Error	3.1255	0.7287	2.6244	2.1335	1.3584	0.5834	1.5236	6.4974
Observations	730	730	730	730	730	730	730	470
Intercept								
Coefficient	0.2757	0.1192	0.2204	0.1055	0.0616	0.0336	0.1223	0.1998
Standard Error	0.1174	0.0682	0.0992	0.0800	0.0511	0.0218	0.0573	0.2999
t Stat	2.3488	1.7493	2.2227	1.3178	1.2048	1.5381	2.1327	0.6662
P-value	0.0191	0.0807	0.0265	0.1880	0.2287	0.1245	0.0333	0.5056
Lower 95%	0.0452	−0.0146	0.0257	−0.0517	−0.0388	−0.0093	0.0097	−0.3895
Upper 95%	0.5061	0.253	0.415	0.2626	0.1619	0.0765	0.2348	0.7890
DTP Variable								
Coefficient	0.0255	−0.2023	0.0737	0.0931	−0.0352	−0.003	0.3207	0.0622
Standard Error	0.0760	0.0920	0.0918	0.0999	0.0955	0.0914	0.1020	0.0589
t Stat	0.3356	−2.1989	0.8029	0.9317	−0.369	−0.0328	3.1430	1.0563
P-value	0.7373	0.0282	0.4223	0.3518	0.7122	0.9738	0.0017	0.2914
Lower 95%	−0.1237	−0.3828	−0.1066	−0.1031	−0.2226	−0.1825	0.1204	−0.0535
Upper 95%	0.1746	−0.0217	0.2540	0.2894	0.1522	0.1765	0.5211	0.1780
ANOVA								
SS	1.1000	15.9185	4.4402	3.9518	0.2513	0.0004	22.9319	47.1055
MS	1.1000	15.9185	4.4402	3.9518	0.2513	0.0004	22.9319	47.1055
F	0.1126	4.835	0.6447	0.8682	0.1362	0.0011	9.8782	1.1158
Significance F	0.7373	0.0282	0.4223	0.3518	0.7122	0.9738	0.0017	0.2914

Table 6. Future prices vs. capitalised prices: individual asset results. Individual regressions of future prices (FP) on capitalised prices (CP): (**a**) in levels $FP_t = \alpha + \beta CP_t + \epsilon_t$ and (**b**) in differences $\Delta FP_t = \alpha + \beta \Delta CP_t + \epsilon_t$.

(**a**) In levels

	Adidas	Anheuser	ASML	Essilor	Fresenius	Inditex	Safran	Volkswagen
Regression Statistics								
Multiple R	0.9404	0.9262	0.9566	0.9487	0.9328	0.9448	0.9697	0.7627
R Square	0.8843	0.8579	0.9150	0.900	0.8702	0.8927	0.9402	0.5818
Adjusted R Square	0.8841	0.8577	0.9149	0.8999	0.8700	0.8925	0.9402	0.5811
Standard Error	19.206	11.567	14.1260	10.3022	7.7464	3.214	7.4152	31.724
Observations	731	731	731	731	731	731	731	679
Intercept								
Coefficient	2.183	9.2317	3.0541	7.5376	5.1339	2.4446	−1.0466	39.3794
Standard Error	1.2048	0.7764	0.8022	0.8199	0.4897	0.2062	0.4568	2.6745
t Stat	1.8119	11.8897	3.8071	9.1934	10.4831	11.8543	−2.2909	14.7239
P-value	0.0704	0.0000	0.0002	0.0000	0.0000	0.0000	0.0223	0.0000
Lower 95%	−0.1823	7.7074	1.4792	5.928	4.1725	2.0397	−1.9434	34.1281
Upper 95%	4.5483	10.7560	4.6291	9.1473	6.0954	2.8494	−0.1497	44.6308
CP Variable								
Coefficient	0.9747	0.7703	0.9547	0.8697	0.8087	0.7918	1.0556	0.5835
Standard Error	0.0131	0.0116	0.0108	0.0107	0.0116	0.0102	0.0099	0.0190
t Stat	74.6454	66.3494	88.6132	81.0032	69.897	77.8717	107.0977	30.6864
P-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Lower 95%	0.9490	0.7475	0.9335	0.8487	0.786	0.7718	1.0363	0.5461
Upper 95%	1.0003	0.7931	0.9758	0.8908	0.8315	0.8118	1.075	0.6208
ANOVA								
SS	2,055,329	588,997	1,566,881	696,404	293,167	62,639	630,679	947,694
MS	2,055,329	588,997	1,566,881	696,404	293,167	62,639	630,679	947,694
F	5572	4402	7852	6562	4886	6064	11,470	942
Significance F	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

(**b**) In differences

	Adidas	Anheuser	ASML	Essilor	Fresenius	Inditex	Safran	Volkswagen
Regression Statistics								
Multiple R	0.0387	0.0390	0.0223	0.0021	0.0246	0.1010	0.0432	0.1214
R Square	0.0015	0.0015	0.0005	0.0000	0.0006	0.0102	0.0019	0.0147
Adjusted R Square	0.0001	0.0002	−0.0009	−0.0014	−0.0008	0.0088	0.0005	0.0126
Standard Error	3.1234	1.8191	2.6249	2.1348	1.3581	0.5805	1.5325	6.4570
Observations	730	730	730	730	730	730	730	470
Intercept								
Coefficient	0.2714	0.0976	0.2309	0.1173	0.0605	0.0303	0.1493	0.1773
Standard Error	0.1161	0.0674	0.0976	0.0792	0.0504	0.0215	0.0569	0.2981
t Stat	2.3382	1.4480	2.3659	1.4817	1.1999	1.4061	2.6235	0.5948
P-value	0.0196	0.1480	0.0182	0.1389	0.2306	0.1601	0.0089	0.5523
Lower 95%	0.0435	−0.0347	0.0393	−0.0381	−0.0385	−0.0120	0.0376	−0.4085
Upper 95%	0.4993	0.2300	0.4224	0.2727	0.1594	0.0725	0.2611	0.7631
DCP Variable								
Coefficient	0.0365	−0.0356	0.0224	0.0020	−0.0249	0.0924	0.0446	0.1026
Standard Error	0.0349	0.0337	0.0373	0.0350	0.0376	0.0337	0.0382	0.0388
t Stat	1.0460	−1.0539	0.6015	0.0571	−0.6629	2.7390	1.1676	2.6450
P-value	0.2959	0.2923	0.5477	0.9545	0.5076	0.0063	0.2434	0.0084
Lower 95%	−0.0320	−0.1018	−0.0508	−0.0668	−0.0988	0.0262	−0.0304	0.0264
Upper 95%	0.1051	0.0307	0.0957	0.0708	0.0489	0.1586	0.1196	0.1788
ANOVA								
SS	10.6731	3.6758	2.4931	0.0149	0.8105	2.5277	3.2016	291.6781
MS	10.6731	3.6758	2.4931	0.0149	0.8105	2.5277	3.2016	291.6781
F	1.0941	1.1108	0.3618	0.0033	0.4394	7.5019	1.3632	6.9958
Significance F	0.2959	0.2923	0.5477	0.9545	0.5076	0.0063	0.2434	0.0084

Table 7. Target prices vs. capitalised prices: individual asset results. Individual regressions of target prices (FP) on capitalised prices (CP): (**a**) in levels $TP_t = \alpha + \beta CP_t + \epsilon_t$ and (**b**) in differences $\Delta TP_t = \alpha + \beta \Delta CP_t + \epsilon_t$.

(**a**) In levels

	Adidas	Anheuser	ASML	Essilor	Fresenius	Inditex	Safran	Volkswagen
Regression Statistics								
Multiple R	0.9907	0.9947	0.9944	0.9910	0.9927	0.9926	0.9909	0.8291
R Square	0.9816	0.9895	0.9889	0.9820	0.9855	0.9852	0.9819	0.6875
Adjusted R Square	0.9815	0.9895	0.9889	0.9820	0.9855	0.9852	0.9819	0.6870
Standard Error	6.2686	3.6153	4.2426	4.4920	2.7701	1.3281	3.2030	32.8506
Observations	731	731	731	731	731	731	731	679
Intercept								
Coefficient	10.3126	7.8353	4.0534	5.7802	2.5836	1.6513	5.5437	50.0617
Standard Error	0.3932	0.2427	0.2409	0.3575	0.1751	0.0852	0.1973	2.7695
t Stat	26.2256	32.2865	16.8234	16.1686	14.7528	19.3773	28.0942	18.0760
P-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Lower 95%	9.5406	7.3589	3.5804	5.0784	2.2398	1.484	5.1563	44.6238
Upper 95%	11.0845	8.3118	4.5264	6.4821	2.9274	1.8186	5.9311	55.4995
CP Variable								
Coefficient	0.8397	0.9501	0.8251	0.9345	0.9223	0.9259	0.8464	0.7598
Standard Error	0.0043	0.0036	0.0032	0.0047	0.0041	0.0042	0.0043	0.0197
t Stat	197.029	261.8558	255.0016	199.6117	222.9159	220.3481	198.7974	38.5915
P-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Lower 95%	0.8313	0.9430	0.8188	0.9253	0.9142	0.9176	0.8380	0.7212
Upper 95%	0.8480	0.9573	0.8315	0.9437	0.9305	0.9341	0.8548	0.7985
ANOVA								
SS	1,525,453	896,221	1,170,423	804,003	381,300	85,646	405,440	1,607,205
MS	1,525,453	896,221	1,170,423	804,003	381,300	85,646	405,440	1,607,205
F	38,820	68,568	65,026	39,845	49,691	48,553	39,520	1489
Significance F	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

(**b**) In differences

	Adidas	Anheuser	ASML	Essilor	Fresenius	Inditex	Safran	Volkswagen
Regression Statistics								
Multiple R	0.3695	0.2876	0.2176	0.1779	0.0904	0.1263	0.2184	0.2012
R Square	0.1366	0.0827	0.0473	0.0316	0.0082	0.0159	0.0477	0.0405
Adjusted R Square	0.1354	0.0815	0.0460	0.0303	0.0068	0.0146	0.0464	0.0384
Standard Error	1.4169	0.7002	1.0338	0.7785	0.5253	0.2346	0.5400	4.9930
Observations	730	730	730	730	730	730	730	470
Intercept								
Coefficient	0.2103	0.1147	0.1950	0.1214	0.0936	0.0346	0.0914	0.1243
Standard Error	0.0527	0.0260	0.0384	0.0289	0.0195	0.0087	0.0201	0.2305
t Stat	3.9943	4.4181	5.0737	4.2036	4.8017	3.9763	4.5579	0.5392
P-value	0.0001	0.0000	0.0000	0.0000	0.0000	0.0001	0,0000	0.5900
Lower 95%	0.1069	0.0637	0.1195	0.0647	0.0553	0.0175	0.0520	−0.3287
Upper 95%	0.3137	0.1656	0.2704	0.1780	0.1318	0.0517	0.1308	0.5773
DCP Variable								
Coefficient	0.1700	0.1052	0.0884	0.0623	0.0356	0.0468	0.0813	0.1332
Standard Error	0.0158	0.0130	0.0147	0.0128	0.0146	0.0136	0.0135	0.0300
t Stat	10.7300	8.1030	6.0144	4.8774	2.4487	3.4341	6.0379	4.4432
P-value	0.0000	0.0000	0.0000	0.0000	0.0146	0.0006	0.0000	0.0000
Lower 95%	0.1389	0.0797	0.0595	0.0372	0.0071	0.0201	0.0548	0.0743
Upper 95%	0.2011	0.1307	0.1172	0.0874	0.0642	0.0736	0.1077	0.1921
ANOVA								
SS	231.1325	32.1946	38.6599	14.4182	1.6545	0.6491	10.6316	492.1667
MS	231.1325	32.1946	38.6599	14.4182	1.6545	0.6491	10.6316	492.1667
F	115.1337	65.6589	36.1726	23.7889	5.9962	11.7931	36.456	19.7418
Significance F	0.0000	0.0000	0.0000	0.0000	0.0146	0.0000	0.0000	0.0000

In general, when considering individual time series, the R^2 for *in difference* regressions increase.

- For each of the eight companies presented, the accuracy is not as bad as in the overall sample; the R^2 levels of the “FP vs TP” regressions range from 0.0012 (Inditex) to 0.1157 (Safran), suggesting that the accuracy of target prices is less than 12%, and varies considerably from firm to firm.
- Similarly, R^2 levels of the “FP vs CP” regressions range from 0.0021 (Essilor) to 0.1214 (Volkswagen), suggesting similar levels of accuracy of the two forecasts with target prices working better for some firms and capitalised prices for others.
- It is interesting that the highest R^2 levels are found for the “TP vs CP” regressions, where the R^2 levels range from 0.0904 (Fresenius) to as high as 0.3685 (Adidas), suggesting that at least between 10% and 35% of target prices can be explained by simple capitalisation rules.

Figures A1–A8 illustrate the individual regression results.

5. Conclusions

Our empirical evidence indicates that, in the European stock market, Bloomberg’s consensus 12-month target prices are not accurate forecasts for future markets prices. It also shows that target prices by analysts do not even "beat" the accuracy of capitalised prices as forecasters of future prices (both do similarly bad).

This is at least the case for large capitalisation stocks, as our sample considers only stocks of the 50 European companies that stayed the longest in the Eurostoxx index between 2004 and 2019. If, as Falkenstein (1996) suggests, research intensity is positively related with accuracy, due to a learning effect, and, analogously, prediction errors are inversely related with some market factors such as size and liquidity, then accuracy for smaller cap companies is expected to be even worse.

Despite the spurious nature of *in level* panel regressions and the extreme low explanatory power of *in difference* regressions, we found evidence that the overall target prices are positively biased, as suggested by Ottaviani and Sørensen (2006), although, based upon our subperiod analysis, that was during the European crisis period (both global financial and sovereign debt), between September 2009 and 2012. In fact, during those times analysts were overall pessimistic.

The individual regression analysis seems to indicate the overall low accuracy may result from considerable variety in individual firm accuracy and size bias. Nonetheless, we still observed that target prices and capitalised prices are just slightly more accurate predictors of future prices and, if anything, capitalised prices seems to do better.

Although possibly polemical, from the industry perspective, our findings are in line with most of the academic literature.

One of the limitations of our analysis is the fact that we rely on Bloomberg consensus 12-month market prices that are averages of individual analysts’ forecasts. As suggested by Palley et al. (2019) and Tiberius and Lisiecki (2019), dispersion across analysts may also play a role. It could also be that a concrete analyst would perform much better (whilst others would need to perform worse) at particular time periods and/or for a particular set of companies. The debate on the performance (and survival) of “star” analysts goes on in the literature (see e.g., Bjerring et al. 1983; Desai et al. 2000).

However, unless the “good” forecasters are always the same , it is unlikely investors would risk following a particular analyst or set of analysts, instead of the industry *consensus*.

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Appendix A

Table A1. Overall panel regression: cross-fixed effects.

	FP vs. TP		FP vs. CP		TP vs. CP	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Dependent Variable	FP	ΔFP	FP	ΔFP	TP	ΔTP
Mean dependent var	38.516	0.070	38.516	0.070	48.456	0.057
S.D. Dependent var	39.241	1.839	39.241	1.839	42.886	1.758
Intercept						
Coefficient	−0. 811	0.069406	4.186	0.068	14.029	0.051
Std. Error	0.179	0.010	0.108	0.010	0.090	0.009
t-Statistic	−4.532	7.212	38.883	7.033	153.288	5.542
Prob.	0.000	0. 0000	0.000	0.000	0.000	0.000
Independent Variable	TP	ΔTP	CP	ΔCP	CP	ΔCP
Coefficient	0.812	0.004	0.857	0.026	0.859	0.080
Std. Error	0.003	0.005	0.002	0.005	0.002	0.005
t-Statistic	246.739	0.757	382.297	5.401	450.965	1.706
Prob.	0.000	0.449	0.000	0.000	0.000	0.000
Regression Statistics						
R-squared	0.843	0.003	0.916	0.004	0.949	0.010
Adjusted R-squared	0.843	0.001	0.916	0.002	0.949	0.009
S.E. Of regression	15.544	1.838	11.350	1.837	9.649	1.750
Sum square resid	8,819,023	123,084	4,701,829	122,988	3,398,162	111,608
Log Likelihood	−152,118	−73,975	−140,624	−73,960	−134,690	−72,188
F-statistic	3928.6	2.014	8007.9	2.588	13,710	7.608
Prob (F-statistic)	0.000	0.000	0.000	0.000	0.000	0.000
Model Statistics						
AIC	8.327	4.056	7.698	4.055	7.373	3.958
BIC	8.339	4.068	7.710	4.067	7.385	3.970
HQC	8.330	4.060	7.701	4.059	7.377	3.962
Residuals Autocorr.						
Durbi–Watson stat	0.022	2.061	0.047	2.061	0.058	2.081

Regression results using panel least squares based upon 36550 balanced panel observations (with a total of 731 periods included and 50 cross-sections) with fixed effects. Panel variables are future prices (FP), target prices (TP) and capitalised prices (CP). Each column represents a specific panel regression as in Equations (4) and (5). We regress FP on TP, FP on CP and TP on CP, both in levels and differences. We report the model selection criteria of Akaike (1973) (AIC), (Schwarz et al. 1978) (SIC) and Hannan and Quinn (1979) (HQC). For residual autocorrelation, we used the panel data generalisation by Bhargava et al. (1982) of the classical Durbin and Watson (1950) statistic.

Table A2. Pre-crisis period panel regressions.

	FP vs. TP		FP vs. CP		TP vs. CP	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Dependent Variable	FP	ΔFP	FP	ΔFP	TP	ΔTP
Mean dependent var	28.077	0.035	28.077	0.035	41.649	0.135
S.D. Dependent var	23.214	1.196	23.214	1.196	35.118	1.750
Intercept						
Coefficient	3.157	0.037	2.220	0.027	0.992	0.124
Std. Error	0.164	0.013	0.143	0.013	0.152	0.019
t-Statistic	19.289	2.873	15.503	2.135	6.527	6.590
Prob.	0.000	0.004	0.000	0.033	0.000	0.000
Independent Variable	TP	ΔTP	CP	ΔCP	CP	ΔCP
Coefficient	0.598	0.017	0.931	0.089	1.464	0.132
Std. Error	0.003	0.007	0.004	0.013	0.004	0.020
t-Statistic	199.172	−2.285	235.154	6.678	348.352	6.775
Prob.	0.000	0.022	0.000	0.000	0.000	0.000
Regression Statistics						
R-squared	0.819	0.001	0.863	0.005	0.933	0.005
Adjusted R-squared	0.819	0.000	0.863	0.005	0.933	0.005
S.E. of regression	9.868	1.195	8.580	1.193	9.107	1.746
Sum square resid	851,841	12,426	643,983	12,370	725,530	26,514
Log Likelihood	−32,446	−13,895	−31,222	−13,876	−31,744	−17,192
F-statistic	39,670	5.220	55,297	4.460	121,349	45.898
Prob (F-statistic)	0.000	0.022	0.000	0.000	0.000	0.000
Model Statistics						
AAIC	7.417	3.195	7.137	3.190	7.256	3.953
SIC	7.418	3.196	7.139	3.192	7.258	3.954
HQC	7.417	3.195	7.138	3.191	7.257	3.953
Residuals Autocorr.						
Durbi–Watson stat	0.027	2.072	0.028	2.067	0.056	1.944

Regression results using panel least squares based upon 8750 balanced panel observations (with a total of 135 periods included and 50 cross-sections). Panel variables are future prices (FP), target prices (TP) and capitalised prices (CP). Each column represents a specific panel regression as in Equation (3). We regress FP on TP, FP on CP and TP on CP, both in levels and differences. We report the model selection criteria of Akaike (1973) (AIC), (Schwarz et al. 1978) (SIC) and Hannan and Quinn (1979) (HQC). For residual autocorrelation, we used the panel data generalisation by Bhargava et al. (1982) of the classical Durbin and Watson (1950) statistic.

Table A3. Crisis period panel regressions.

	FP vs. TP		FP vs. CP		TP vs. CP	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Dependent Variable	FP	ΔFP	FP	ΔFP	TP	ΔTP
Mean dependent var	26.324	0.038	26.324	0.038	41.647	0.073
S.D. Dependent var	22.156	1.582	22.156	1.582	33.856	2.539
Intercept						
Coefficient	5.468	0.038	2.480	0.038	3.087	0.072
Std. Error	0.213	0.015	0.158	0.015	0.187	0.024
t-Statistic	25.705	2.557	15.672	2 557854	16.495	−3.008
Prob.	0.000	0.011	0.000	0.011	0.000	0.003
Independent Variable	TP	ΔTP	CP	ΔCP	CP	ΔCP
Coefficient	0.501	0.000	0.816	0.001	1.320	0.026
Std. Error	0.004	0.006	0.004	0.008	0.005	0.013
t-Statistic	126.367	0.057	194.373	0.117	265.826	1.947
Prob.	0.000	0.954	0.000	0.907	0.000	0.052

Table A3. *Cont.*

	FP vs. TP		FP vs. CP		TP vs. CP	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Regression Statistics						
R-squared	0.586	0.000	0.770	0.000	0.862	0.000
Adjusted R-squared	0.586	0.000	0.770	0.000	0.862	0.000
S.E. of regression	14.262	1.582	10.631	1.582	12.570	2.539
Sum square resid	2,298,141	28,138	1,276,771	28,138	1,785,249	72,490
Log Likelihood	−46,064	−21,120	−42,743	−21,120	−44,637	−26,443
F-statistic	15,969	0.003	37,781	0.014	70,664	3.791
Prob (F-statistic)	0.000	0.954	0.000	0.907	0.000	0.052
Model Statistics						
AIC	8.153	3.755	7.566	3.755	7.901	4.701
SIC	8.155	3.756	7.567	3.756	7.902	4.703
HQC	8.154	3.755	7.566	3.755	7.901	4.702
Residuals Autocorr.						
Durbi–Watson stat	0.0203	2.2066	0.0417	2.2067	0.0761	2.2790

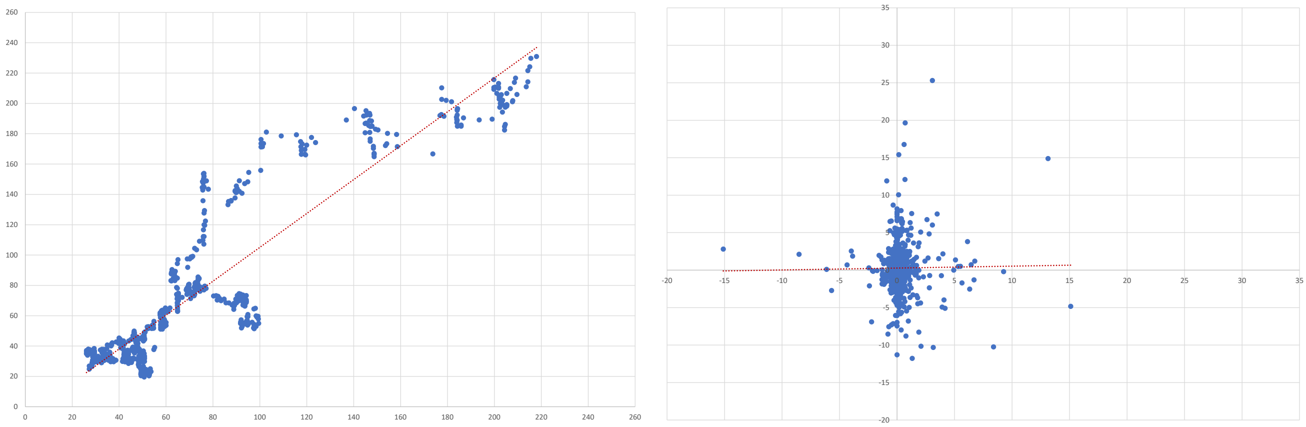
Regression results using panel least squares based upon 11300 balanced panel observations (with a total of 226 periods included and 50 cross-sections). Panel variables are future prices (FP), target prices (TP) and capitalised prices (CP). Each column represents a specific panel regression as in Equation (3). We regress FP on TP, FP on CP and TP on CP, both in levels and differences. We report the model selection criteria of Akaike (1973) (AIC), (Schwarz et al. 1978) (SIC) and Hannan and Quinn (1979) (HQC). For residual autocorrelation, we used the panel data generalisation by Bhargava et al. (1982) of the classical Durbin and Watson (1950) statistic.

Table A4. Post-crisis period panel regressions.

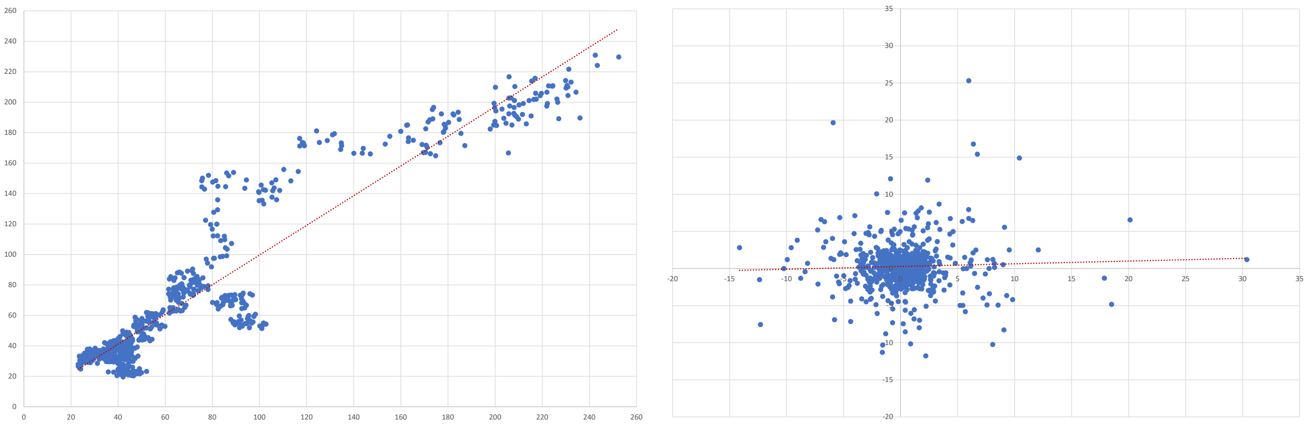
	FP vs. TP		FP vs. CP		TP vs. CP	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Dependent Variable	FP	ΔFP	FP	ΔFP	TP	ΔTP
Mean dependent var	52.401	0.107	52.401	0.107	56.730	0.106
S.D. Dependent var	49.365	2.242	49.365	2.242	50.105	0.895
Intercept						
Coefficient	−1.026	0.098	2.701	0.103	5.021	0.093
Std. Error	0.170	0.018	0.150	0.017	0.090	0.007
t-Statistic	−6.016	5.562	18.063	5.862	55.952	13.744
Prob.	0.000	0.000	0.000	0.000	0.000	0.000
Independent Variable	TP	ΔTP	CP	ΔCP	CP	ΔCP
Coefficient	0.942	0.086	0.919	0.033	0.957	0.097
Std. Error	0.002	0.020	0.002	0.007	0.001	0.003
t-Statisti	418.079	4.406	459.943	4.518	797.498	34.875
Prob.	0.000	0.000	0.000	0.000	0.000	0.000
Regression Statistics						
R-squared	0.914	0.001	0.928	0.001	0.975	0.069
Adjusted R-squared	0.914	0.001	0.928	0.001	0.975	0.069
S.E. of regression	14.498	2.241	13.278	2.241	7.967	0.864
Sum square resid	3,467,636	82,572	2,908,700	82,567	1,047,283	12,266
Log Likelihood	−67,532	−36,611	−66,082	−36,611	−57,655	−20,927
F-statistic	174,790	1.941	211,548	2.041	636,003	1216
Prob (F-statistic)	0.000	0.000	0.000	0.000	0.000	0.000
Model Statistics						
AIC	8.186	4.451	8.010	4.451	6.989	2.545
SIC	8.187	4.452	8.011	4.452	6.990	2.546
HQC	8.186	4.452	8.011	4.452	6.989	2.545
Residuals Autocorr.						
Durbi–Watson stat	0.027	2.009	0.054	2.005	0.079	1.306

Regression results using panel least squares based upon 16500 balanced panel observations (with a total of 330 periods included and 50 cross-sections). Panel variables are future prices (FP), target prices (TP) and capitalised prices (CP). Each column represents a specific panel regression as in Equation (3). We regress FP on TP, FP on CP and TP on CP, both in levels and differences. We report the model selection criteria of Akaike (1973) (AIC), (Schwarz et al. 1978) (SIC) and Hannan and Quinn (1979) (HQC). For residual autocorrelation, we used the panel data generalisation by Bhargava et al. (1982) of the classical Durbin and Watson (1950) statistic.

(**a**) FP vs. TP



(**b**) FP vs. CP



(**c**) TP vs. CP

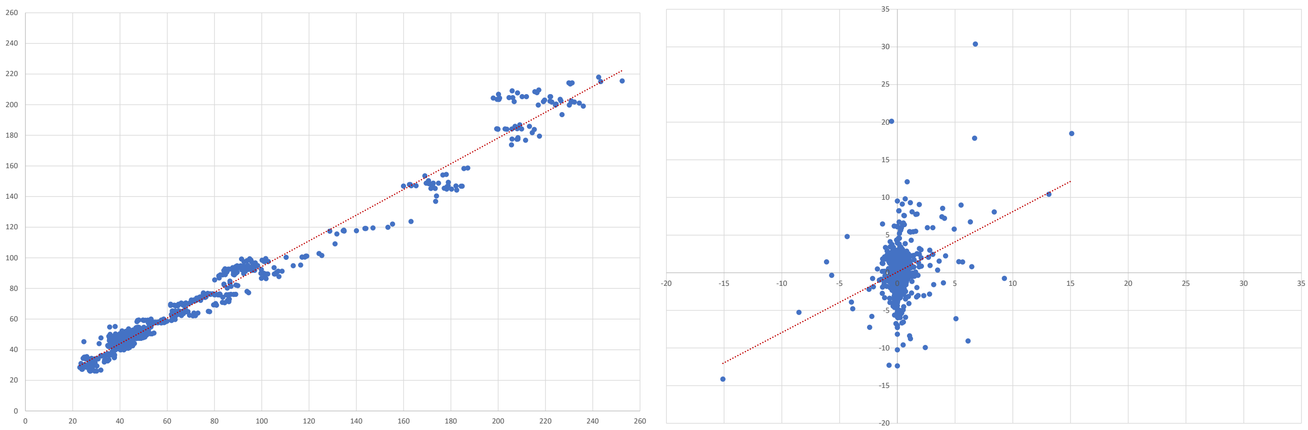
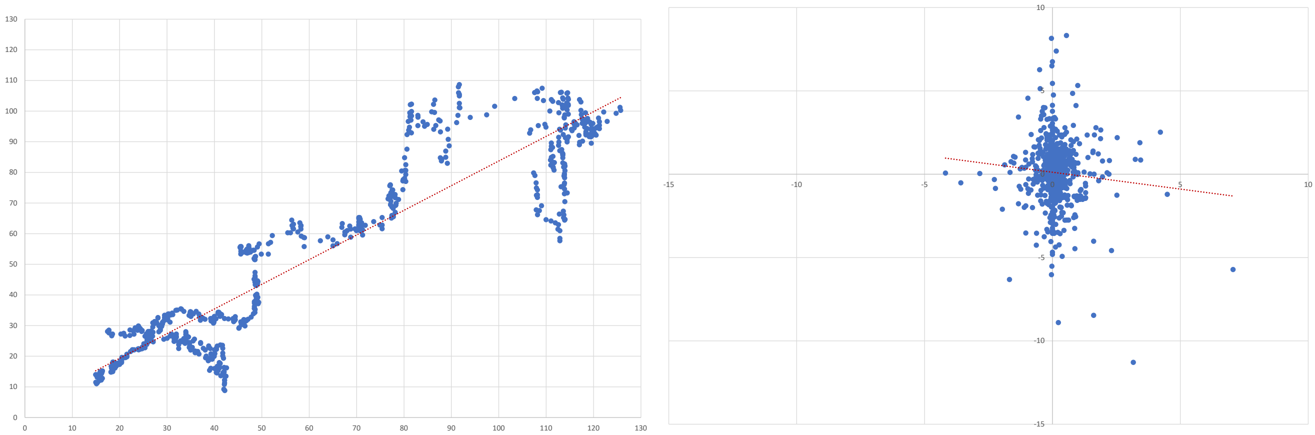
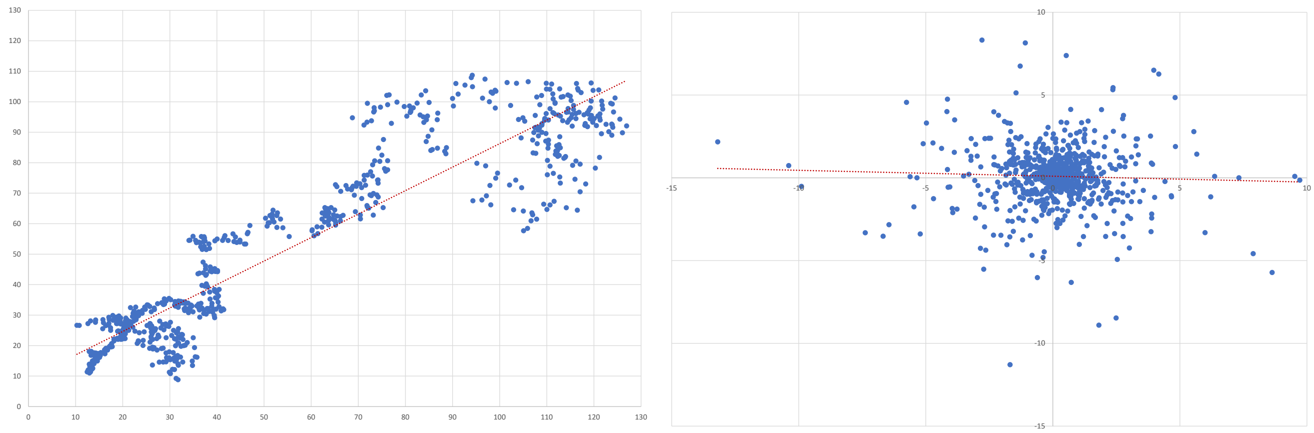


Figure A1. Adidas. Individual time series regressions using three price series on Adidas: future prices (FP), target prices (TP), and capitalised prices (CP) forecasts. On the left-hand-side are images of level regressions and on the right-hand-side are the regressions in differences.

(**a**) FP vs. TP



(**b**) FP vs. CP



(**c**) TP vs. CP

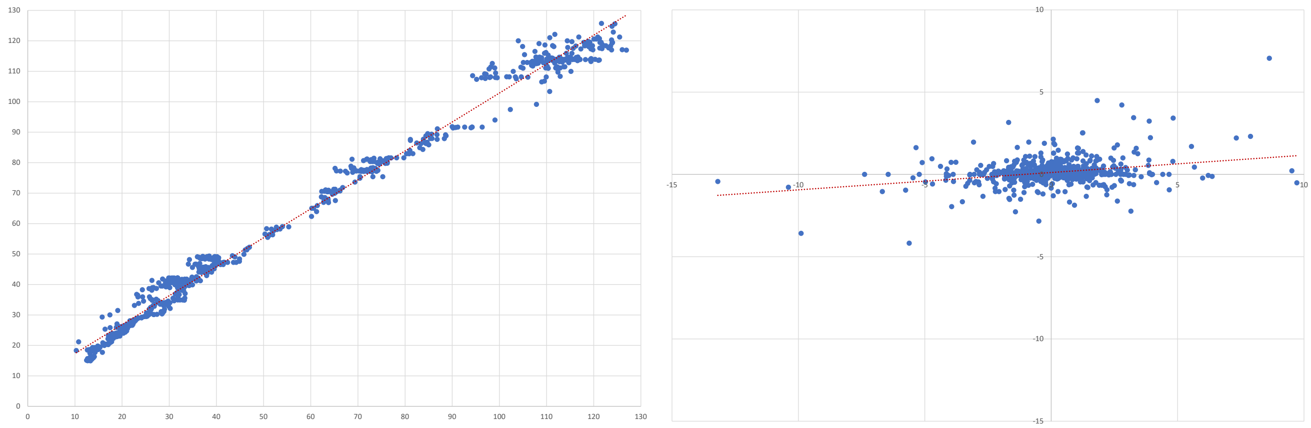
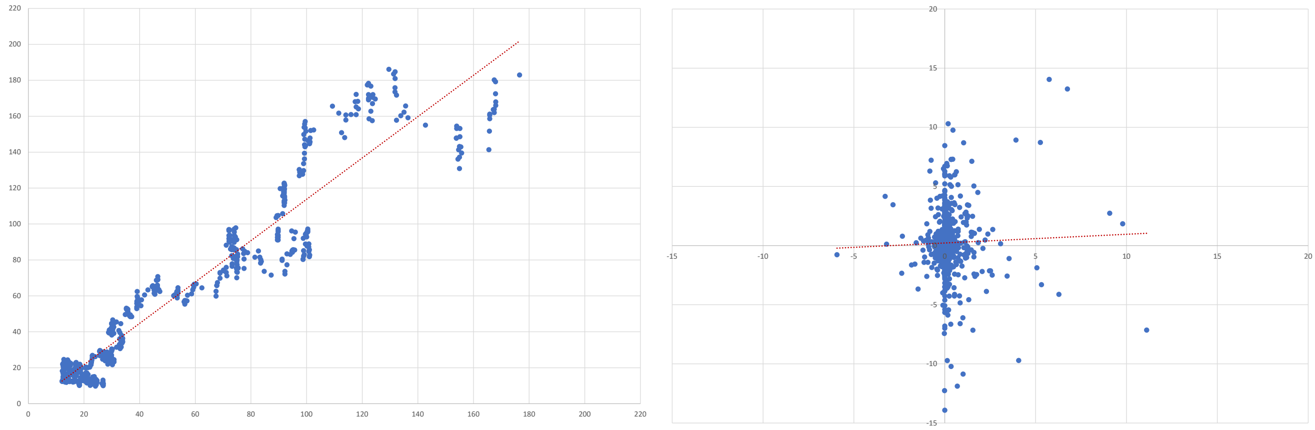
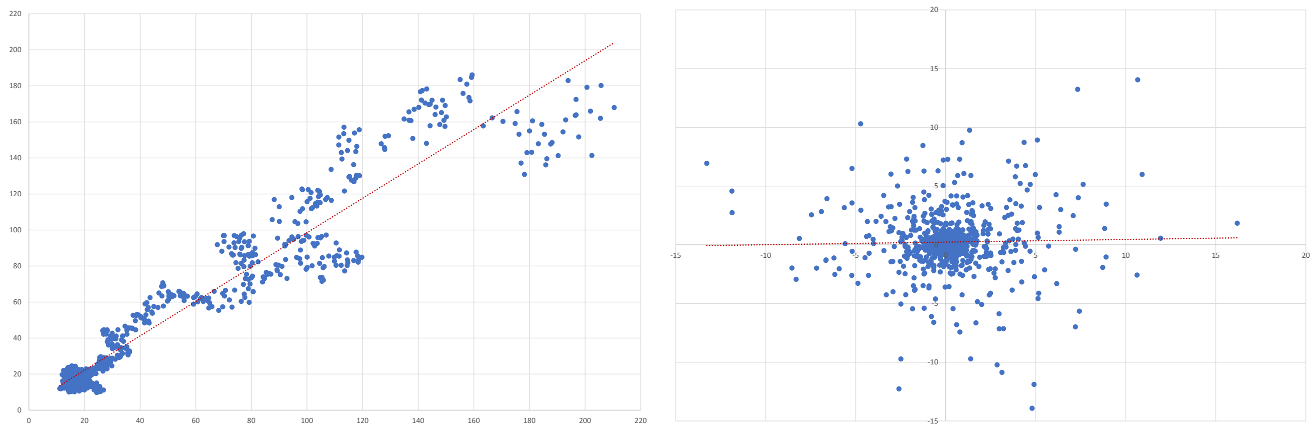


Figure A2. Anheuser. Individual time series regressions using three price series on Anheuser: future prices (FP), target prices (TP), and capitalised prices (CP) forecasts. On the left-hand-side images of level regressions and on the right-hand-side of regressions in differences.

(**a**) FP vs. TP



(**b**) FP vs. CP



(**c**) TP vs. CP

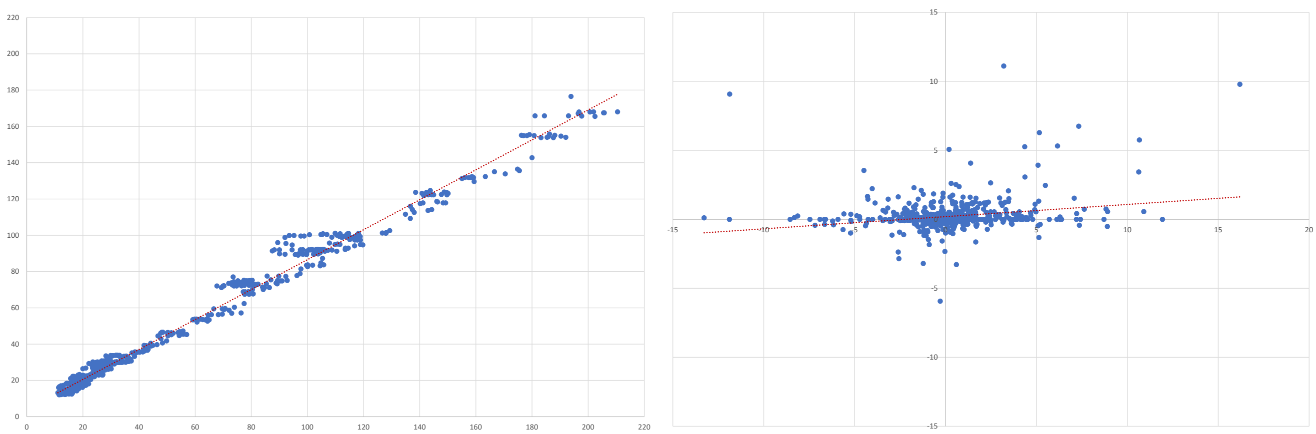
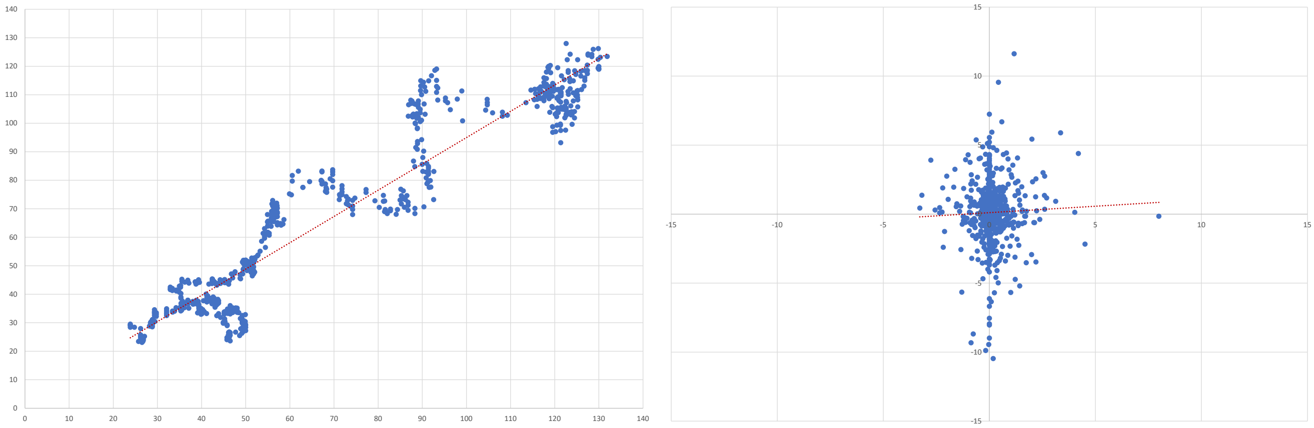
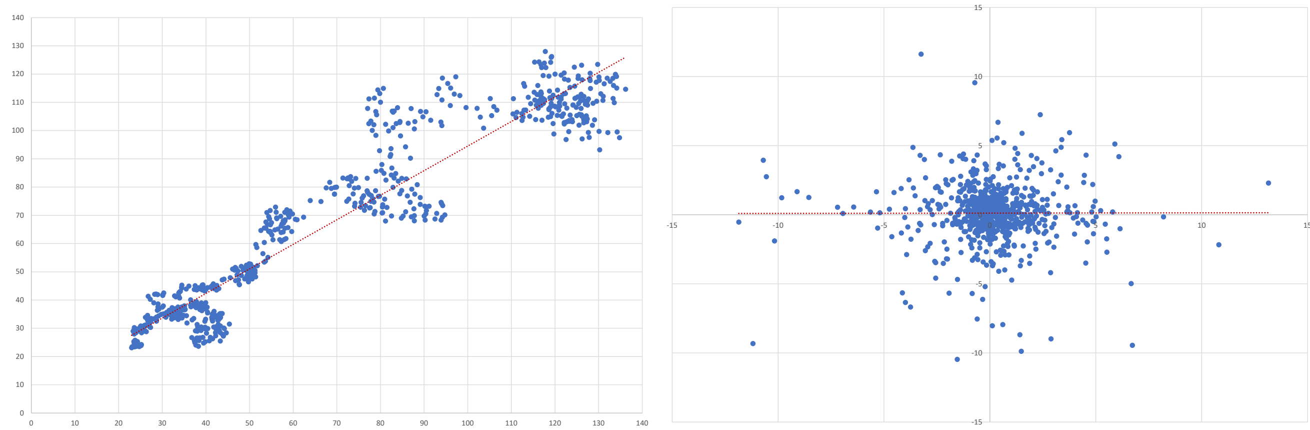


Figure A3. ASML. Individual time series regressions using three price series on ASML: future prices (FP), target prices (TP), and capitalised prices (CP) forecasts. On the left-hand-side are images of level regressions and on the right-hand-side are regressions in differences.

(**a**) FP vs. TP



(**b**) FP vs. CP



(**c**) TP vs. CP

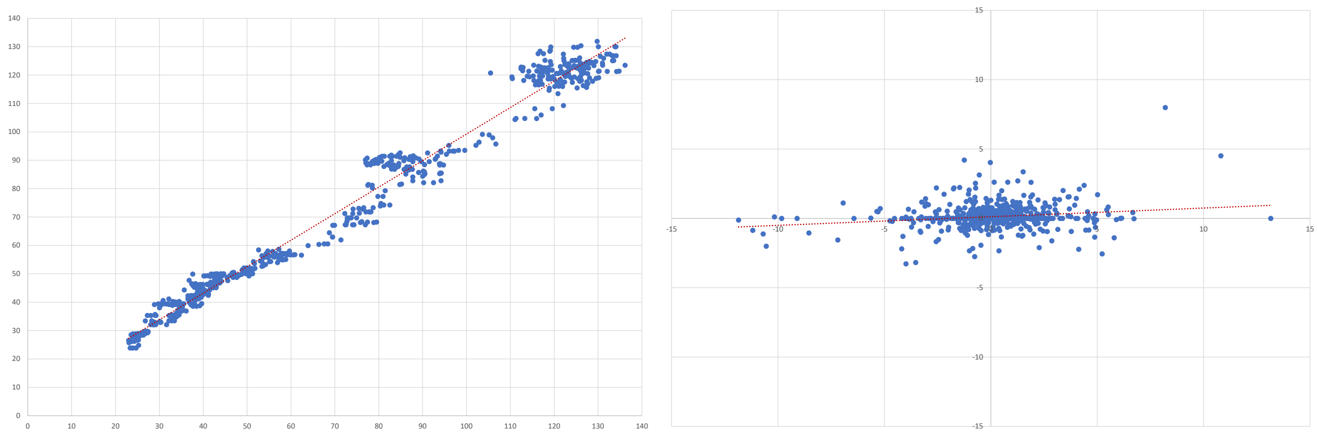
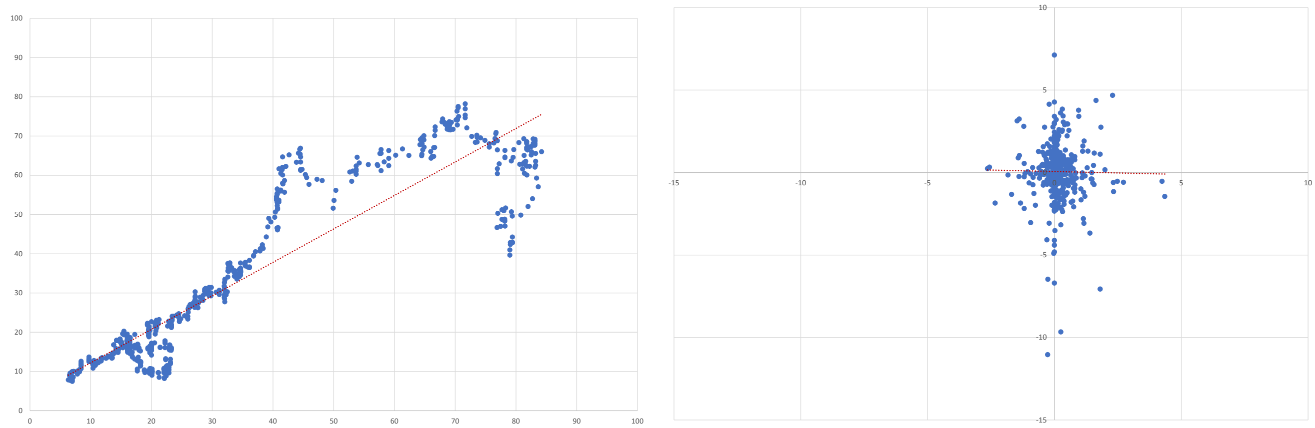
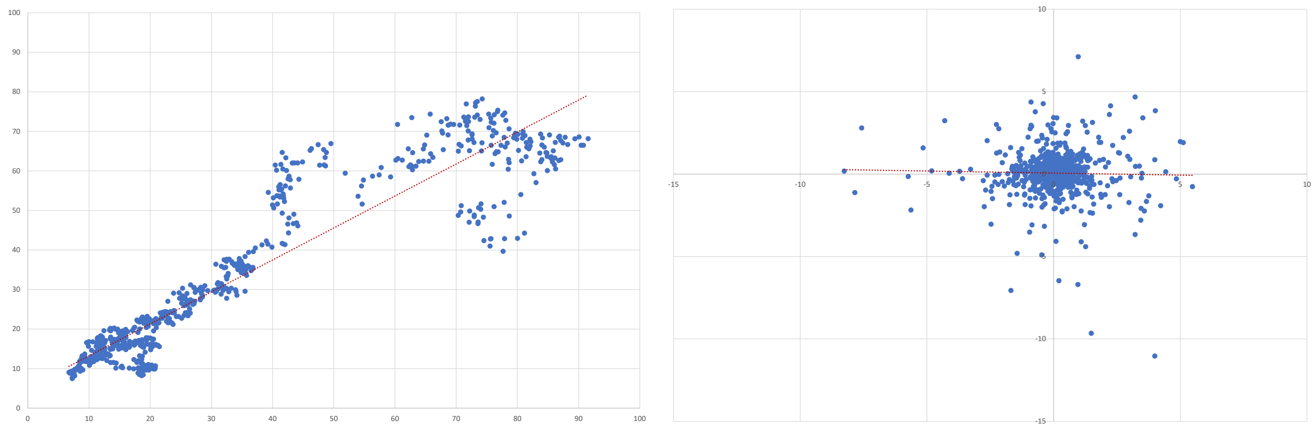


Figure A4. Essilor. Individual time series regressions using three price series on Essilor: future prices (FP), target prices (TP), and capitalised prices (CP) forecasts. On the left-hand-side are images of level regressions and on the right-hand-side are regressions in differences.

(**a**) FP vs. TP



(**b**) FP vs. CP



(**c**) TP vs. CP

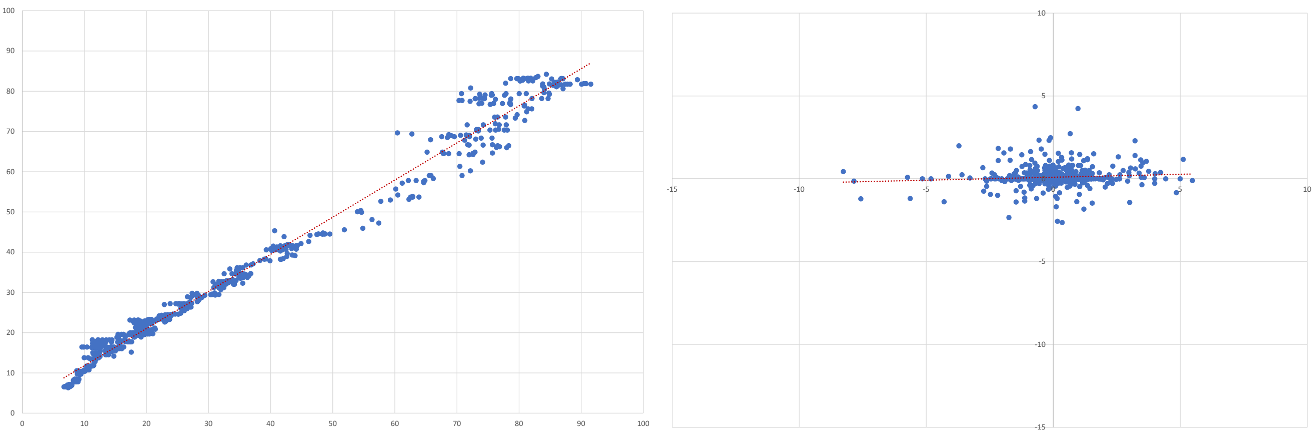
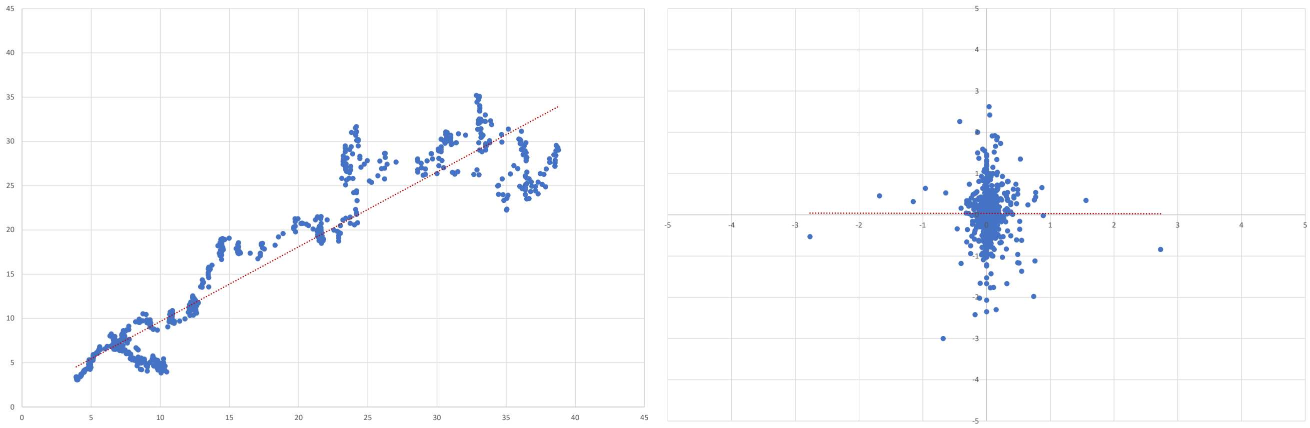
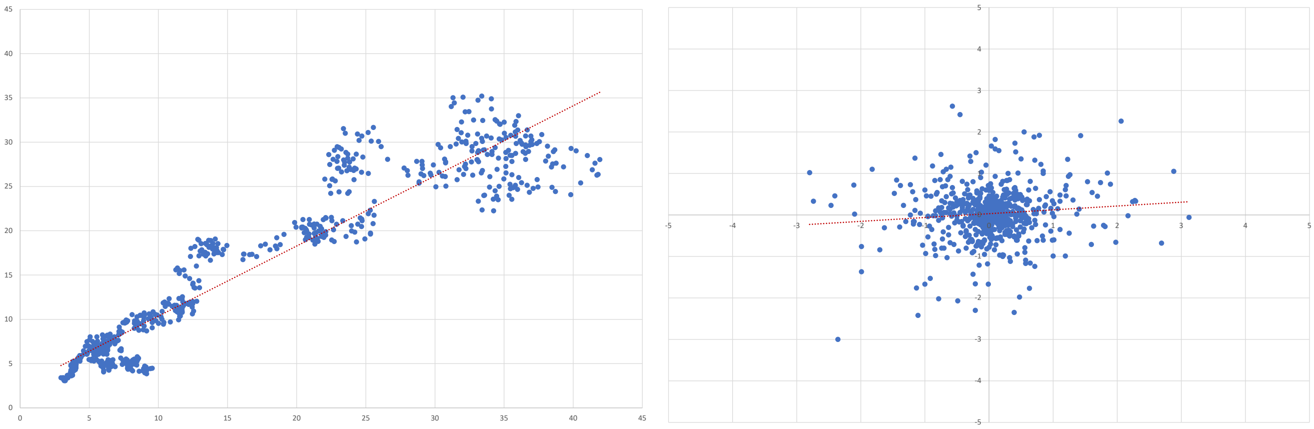


Figure A5. Fresenius. Individual time series regressions using three price series on Fresenius: future prices (FP), target prices (TP), and capitalised prices (CP) forecasts. On the left-hand-side are images of level regressions and on the right-hand-side are regressions in differences.

(**a**) FP vs. TP



(**b**) FP vs. CP



(**c**) TP vs. CP

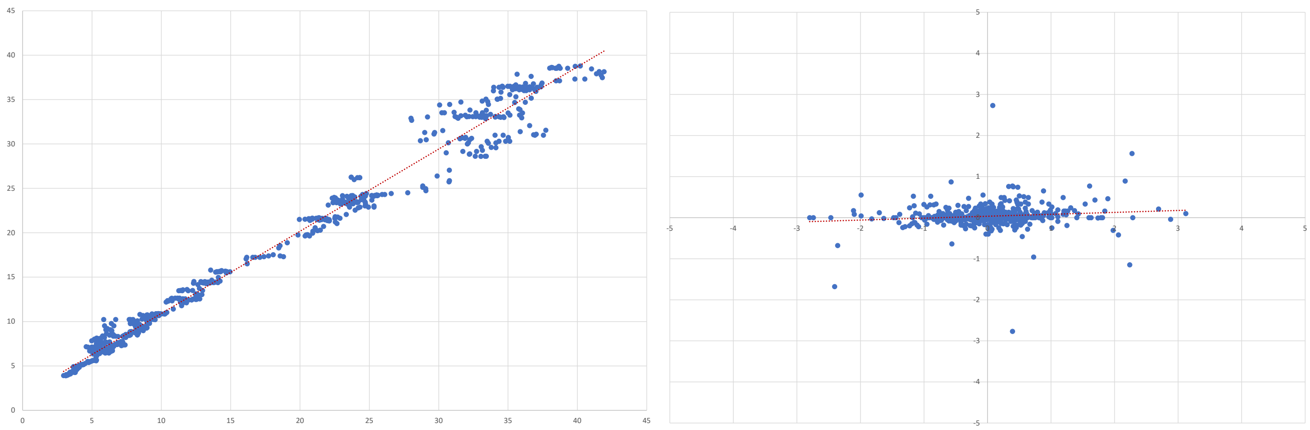
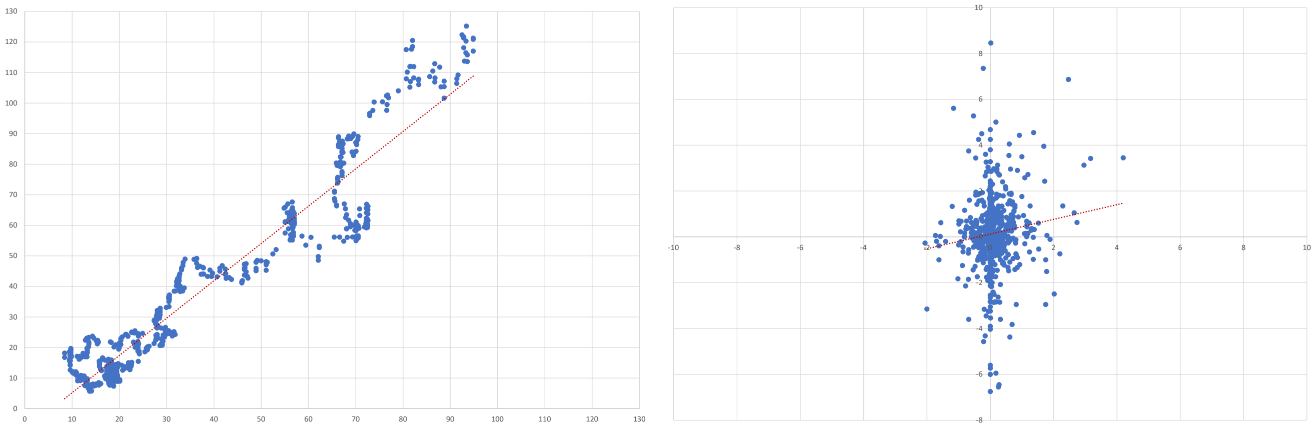
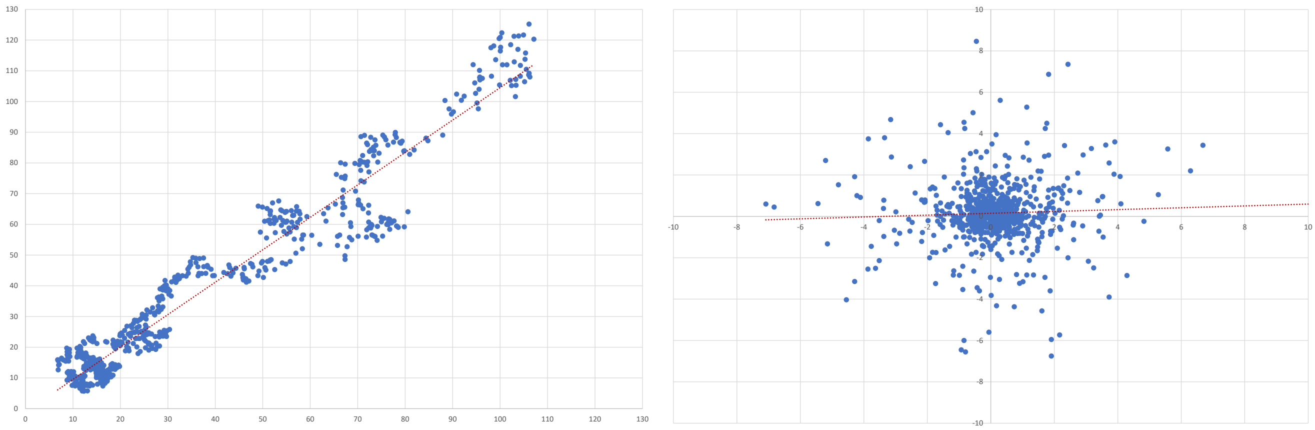


Figure A6. Inditex. Individual time series regressions using three price series on Inditex: future prices (FP), target prices (TP), and capitalised prices (CP) forecasts. On the left-hand-side are images of level regressions and on the right-hand-side are regressions in differences.

(**a**) FP vs. TP



(**b**) FP vs. CP



(**c**) TP vs. CP

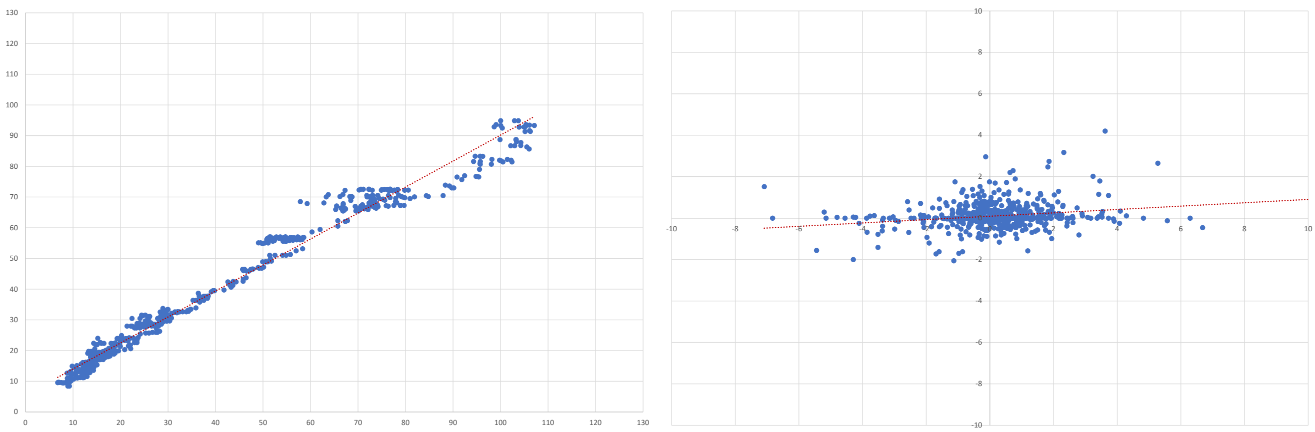
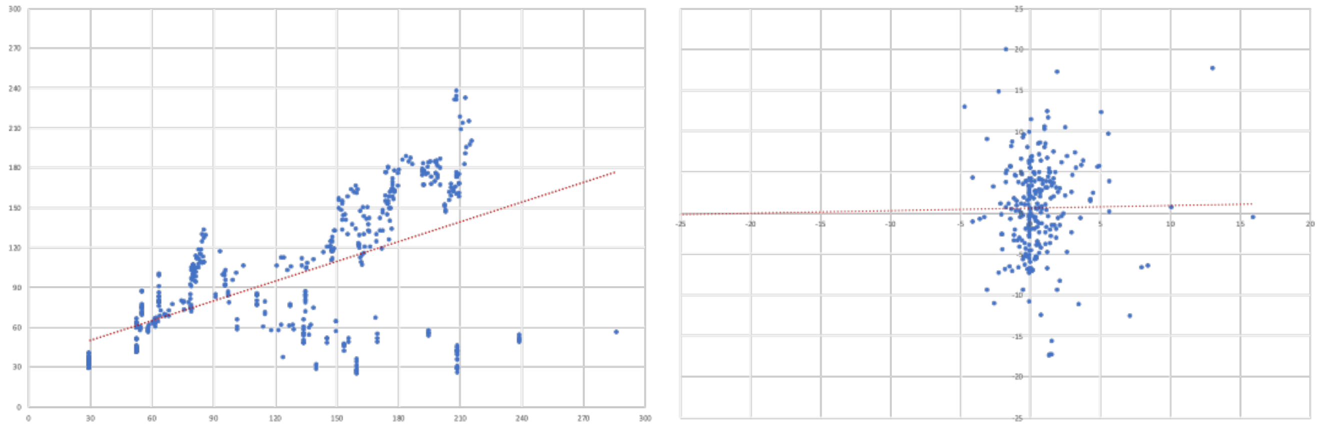
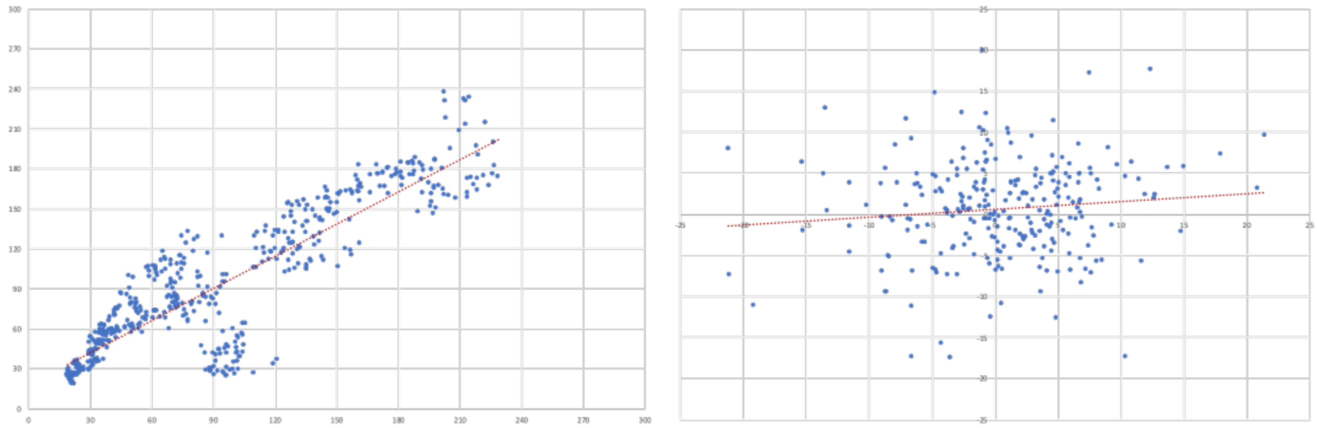


Figure A7. Safran. Individual time series regressions using three price series on Safran: future prices (FP), target prices (TP), and capitalised prices (CP) forecasts. On the left-hand-side are images of level regressions and on the right-hand-side are regressions in differences.

(**a**) FP vs. TP



(**b**) FP vs. CP



(**c**) TP vs. CP

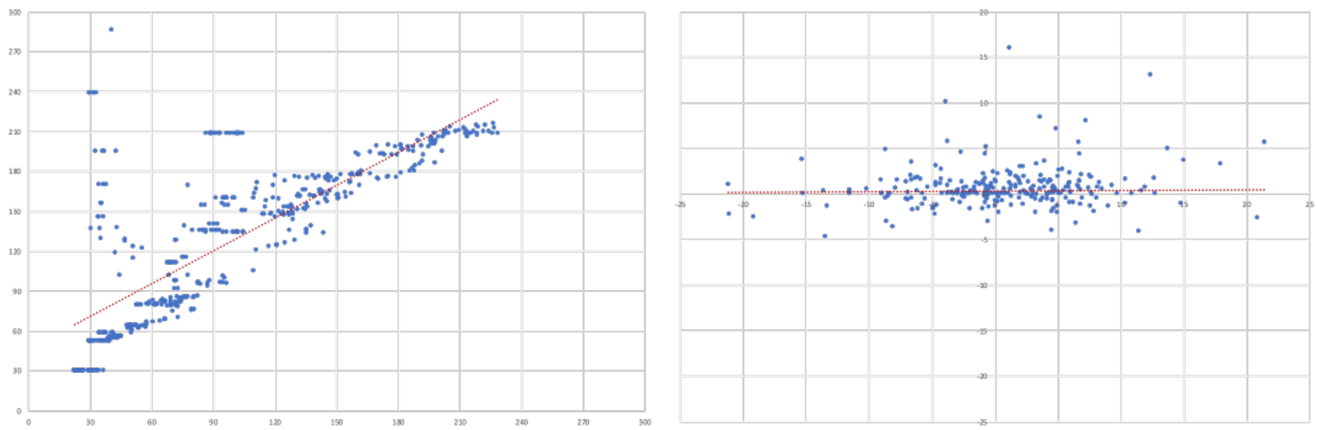


Figure A8. Volkswagen. Individual time series regressions using three price series on Volkswagen: future prices (FP), target prices (TP), and capitalised prices (CP) forecasts. On the left-hand-side are images of level regressions and on the right-hand-side are regressions in differences.

Notes

1 "Order of integration" is a summary statistic used to describe a unit root process in time series analysis. Specifically, it tells you the minimum number of differences needed to obtain a stationary series (Engle and Granger 1991).

2 Our crisis period includes both the global financial crisis and the European sovereign debt crisis.

3 According to Granger and Newbold (2001), we should suspect that a regression is spurious if $R^2 > d$, where d is the Durbin–Watson statistic, which is the case for all level regressions and not the case for the regressions in differences.

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