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Abstract

Equity researches 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 over future market prices. Panel results are robust to company fixed effects and sub-period 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 in forecasting, than simple capitalisations. More interestingly, by analysing also the relationship between both measures – target prices and capitalised prices – we find evidence that capitalised prices partially explain how target prices are determined.

Even when considering individual regressions, accuracy is still very low, but varies considerably across stocks.

KEYWORDS: Target prices, forecast accuracy, panel data analysis.

JEL CODES: C33, G14, G17, G24

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 its is possible to "beat" the market, by investing according to their advise.

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These analysis 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 you 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 general statistics also provided by financial data platforms.

In this study we use Bloomberg's *12–month consensus target prices* for 50 of the highest captitalisation European stocks, over the past 15 years and look into their predictive power.

We use panel regressions to study analysts' target prices accuracy for the European stock market. Besides Bonini et al. (2010), that focus 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 to the consideration of firm-specific fixed effects and sub-period analysis. Concretely we look at three sub-periods: pre-crise period (until the end of August 2008), crise (between September 2008 and end of 2012) and post-crise period (from 2013 onwards). Despite their consistently bad accuracy of target prices, no matter the sub-period, it we found analysts were pessimist over the crise, contradicting the full-sample results where we attest their, previously well documented optimism.

The remaining 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 discuss 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 on-going debate about passive *versus* active portfolio management, or even 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) or Cao et al. (2017), or Elton et al. (2019), to mention just a few over time.

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 analyst 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.

Besides 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 (2007), 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 and in turn push the price in the predicted direction. The self-fulfilling prophecy argument as 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 influences significantly the behavior of investors, in our view, supporting the self-fulling argument.

Early investigations on markets 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, Lys and Sohn (1990) present evidence consistent with forecast revisions having information content (see also Stickel (1991)).

Later studies on target prices' informativeness examine their predictability either in the short term or long term. While they unanimously document a significant short-term market reaction to the release of target prices (Brav and Lehavy, 2003; Asquith et al., 2005; Bradshaw et al., 2013), many find little evidence of target prices' long-term predictability (Bonini et al., 2010; Da and Schaumburg, 2011; Bradshaw et al., 2013).

Indeed, Bonini et al. (2010) find that analysts' forecasting ability of target prices is limited. And Bradshaw et al. (2013) find no evidence of persistence in forecasting accuracy of target prices. On the contrary, covering data from 16 countries, Bilinski et al. (2013) provide 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 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 point to possible very low accuracy levels .

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

3 Data & Methodology

3.1 Data

This study focuses on stock of 50 major (high capitalization) European companies. From all the constituents of EURO STOXX 50 index during the past 15 years, we chose the 50 companies that *stayed the longest* in the index. Concretely, we look at the companies listed in Table 1.

From Table 1 it is clear we do not focus in any particular country or sector, as the listed companies belong to variety of country and all sort of sectors, from Air Fright & Logistics; Airspace & Defense;

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

Automobile manufactures; Chemicals; Construction & Engineering; Consumer durables & Apparel; Diversified chemicals; Diversified banks; Electric Components & Equipment; Electric Utilities; Food Products; Food, beverage & Tobacco; Health Care Equipments; Industrial Conglomerates; Integrated Oil & Gas; Integrated Telecommunication Services; Movies & Entertainment; Multi-line Insurance; Personal Products; Pharmaceuticals; Real State; Reinsurance; Retailing; Semiconductors, Software; Technology Hardware & Equipment; to Hypermarkets, supermarkets, convenience stores, cash & 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 2004-04-27 until 2019-04-23, providing us with a total of 78,300 observations (783 observations our each variable and stock).

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 obtained market prices observed one year before.

Definition 3.1. 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 $P_{i,t-52}$ 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 which extent can 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 in target prices actually result from simple capitalisation rules.

Table 2: Panel unit root test results

	Future Prices (FP)		TargetPrices (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, Lin, and Chu, 2002), that as null hyphothesis assumes common unit root process, and IPS (Im, Pesaran, and Shin, 2003), Fisher-type (Choi, 2001) tests that as null hypothesis assume individual unit root process. Considering a cross-section of 50 time series, individual effects 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 as assymptotic Chi-square distribution. All other tests assume asymptotic normality.

Thus, we look into three types of pairwise relationships:

(A) FP versus TP, we evaluate the accuracy of TP forecasts made by analysts.

(B) FP versus CP, to compare the accuracy of a forecast as naive as CP to analysts TP forecast.

(C) TP versus CP, to evaluate to which 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 represents a u_{it} 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 3.1, whenever we are considering *in level* panel regressions. For *in difference* panel regressions, we consider accordingly, its differences $\Delta FP_{it} = FP_{it} - FP_{i,t-1}$, $\Delta TP_{it} = TP_{it} - TP_{i,t-1}$, and $\Delta CP_{it} = CP_{it} - CP_{i,t-1}$.

Table 2 and the correlograms in the appendix (Figure A1) show that our *panel variables* – FP, TP and CP are non-stacionary. In fact, In fact, the are integrated of other one[1].

Therefore, when regressing our level panel variables on one another, one needs to be very careful with interpretations, as mostly likely they are spurious relationships. For further discussion on spurious relationship identification, see, for instance Granger et al. (2001).

Nonetheless, intercept coefficients of *level regressions* can be interpreted as optimism/pessimism indicators (forecast bias), when we use target prices as predictors of future prices.

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

[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 get a stationary series (Engle and Granger, 1991).

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 evaluate the overall panel regression results in two way: by considering individual company fixed effects and by performing sub-period panel regressions.

To model individual company heterogeneity, we assume that the error term in (3) has two separate components, one of which, μ_i is firm-specific and does not change over time,

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

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

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 to have the individual component to be 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 slang μ_i are called *fixed effects* (a.k.a. within or least squares dummy variables) model, estimated by OLS on transformed data, guaranteeing consistent estimates for β.

Testing robustness of results from a different perspective, we also perform classical panel regressions (as in (3)), but instead of the full sample we consider three different sub-periods:

- the *pre-crise period*, until the end of August 2008,
- the *crise period*, from September 2008 until the end of 2012, and
- the *pots crise period*, from 2013 onwards.

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 form

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

Figure 1 shows the evolution of the three variables – future prices (FP), target prices (TP) and capitalised prices (CP) – for the 8 best performing companies over the 15–year period of our sample. Their non-stationary is also clear.

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) forecasts *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). We choose to report the results on both in level and in difference regressions.

As previously discussed level regressions should be interpreted with extreme care, as we are dealing with non-stationary variables (recall results in Table 2), and the relationships are, as expected, indeed spurious. The extremely small Durbin-Watson statistic value of the level regressions reported in Table 3 (0.019, 0.047 and 0.037) their spurious nature[2]. In practical terms this means that, based upon level regressions we cannot that conclusions on 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 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 Sörensen (2006), in line with Bonini et al. (2010) results.

In terms of forecast accuracy what can be interpreted are the results for the regressions in differences. Form 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 – 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 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 – fourth column of results in able 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.
- we also find that 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.

[2] According to Granger et al. (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.

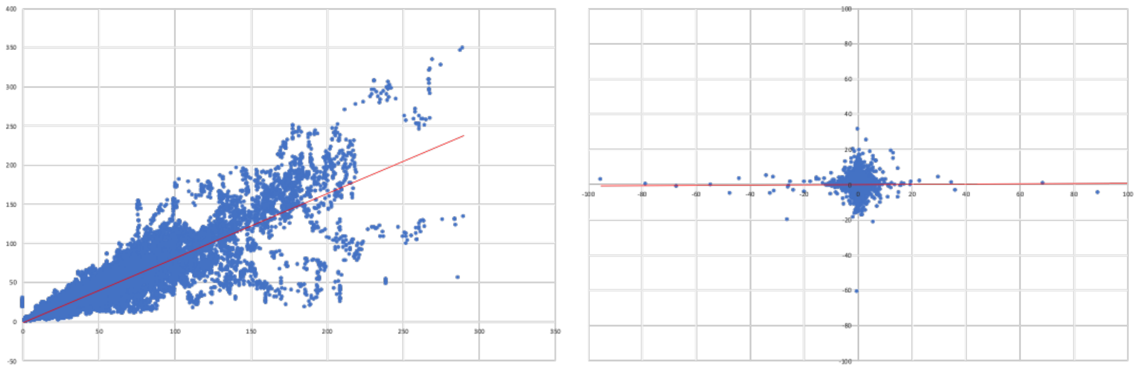
Table 3: Overall Panel Regressions

	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	123419.8	4977847	123309.2	6295006	111837.6
Log Likelihood	-155501.3	-740254.9	-141666.9	-74008.5	-145957.1	-72226.4
F-statistic	157280.5	1.476	376676.4	34.241	353723.7	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

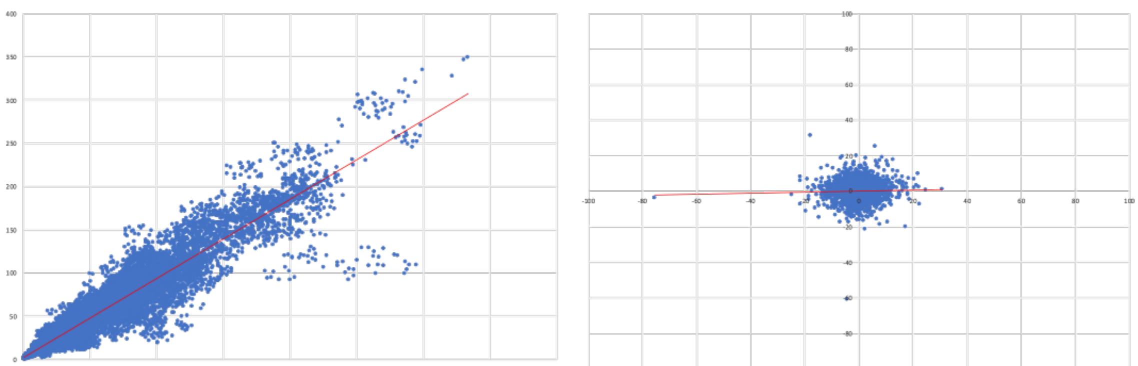
Regression results using panel least squares based upon 36550 balanced panel observations (with a total of 731 periods included and 50 cross-sections). Panel variables are future prices (FP), target prices (TP) and capitalised prices (CP). Each column represents a specific panel regression as in Equation (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 generalization by Bhargava et al. (1982) of the classical Durbin and Watson (1950) statistic.

Figure 2: Panel Regression

(a) FP vs TP



(b) FP vs CP



(c) TP vs CP

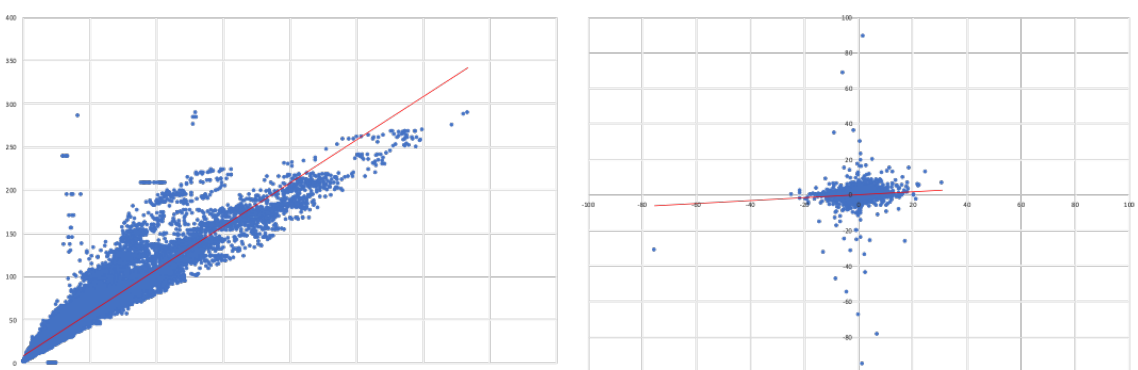


Illustration of the panel regressions of Table 3. On the left-hand-side images of level regressions and on the right-hand-side of regressions in differences.

4.2 Panel robustness

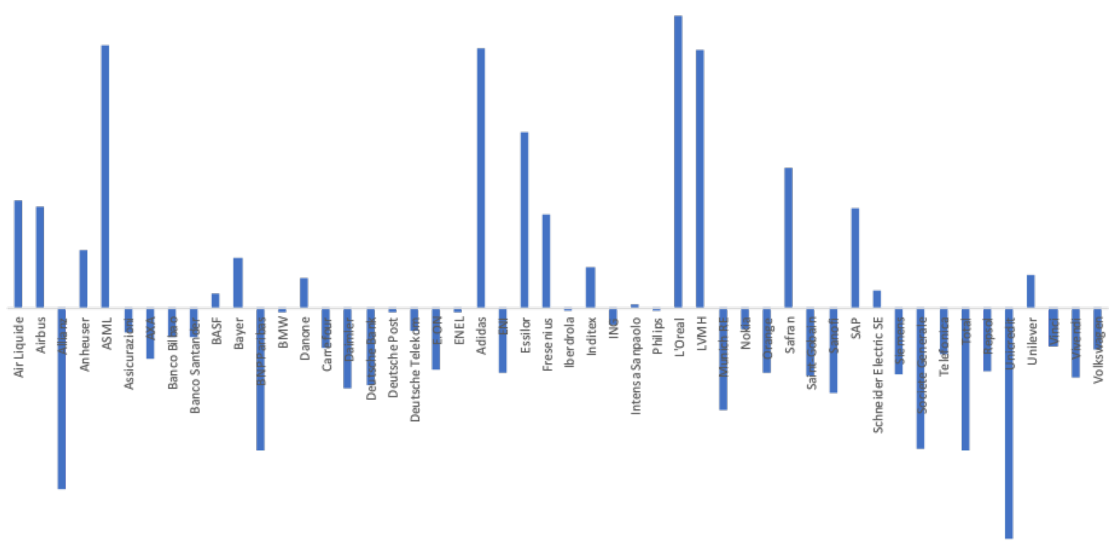
Considering company fixed effects does not change considerably the "picture", in terms of accuracy (see in difference columns (2),(4) and (6) of Table A1, in the appendix), so it seems

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

As before the in level regressions (columns (2),(4) and (6) of Table A1, in the appendix) are spurious. However, looking deeper into the variation 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 get a wide range of μ_i values.

Figure 3: Company fixed effects



Results also do no change much, when considering panel regressions over the three proposed sub-periods: pre-crisis, crise and post-crises.

Table 4 summarises the relevant statistics on the sub-period panel regressions (see full results for each of the sub-periods in Tables A2, A3 and A4, in the appendix). Looking across periods its seems

- analysts became particularly pessimistic during the crise-period (positive and significative $\alpha = 5.4675$ crise period level intercept), and optimist in the post-crise period (negative and significative $\alpha = -1.02577$ for the equivalent post-crise intercept),

- absence of accuracy, of both target prices and capitalised prices got even more severe during the crisis period (lowest adjusted-R^2)

Table 4: Summary of subperiod panel regression results

	Pre-crise	Crise	Post-crise
Panel A: FP vs TP			
In level (1)			
Intercept	3.15669***	5.467543***	-1.025766***
In Differences (2)			
Intercept	0.036918***	0.038144	0̇097836***
Independent Variable	0.016726**	0̇000336	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-crise	Crise	Post-crise
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

4.3 Individual Regressions

Perhaps most interesting are the individual sample results. Tables 5 – 7 show individual time series regressions, for the 8 best performing companies (the ones in Figure 1).

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

- For each of the individual companies considered, 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 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 doing better to some firms, and capitalised prices to other.
- Interesting, is the fact 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 has high as 0.3685 (Adidas), suggesting that at least between 10% to 35% of target prices can be explained by simple capitalisation rules.

Figures A2 – A9 illustrate the individual regression results.

Table 5: Future Prices versus Target Prices: individual asset results

(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	1,11674	0,8049	1,1506	0,92250	0,85320	0,84368	1,22150	0,45112
Standard Error	0,01846	0,0123	0,0130	0,01136	0,01400	0,01144	0,01348	0,02699
t Stat	60,49174	65,4910	88,6353	81,19745	60,94777	73,75920	90,64759	16,71201
P-value	0,00000	0,0000	0,0000	0,00000	0,00000	0,00000	0,00000	0,00000
Lower 95%	1,08049	0,7808	1,1251	0,90020	0,82572	0,82123	1,19505	0,39812
Upper 95%	1,15298	0,8290	1,1761	0,94481	0,88068	0,86614	1,24796	0,50413
ANOVA								
SS	1938121,5127	586797,3605	1566947,1621	696736,6146	281639,8382	61877,8374	616104,0107	475770,5434
MS	1938121,5127	586797,3605	1566947,1621	696736,6146	281639,8382	61877,8374	616104,0107	475770,5434
F	3659,2505	4289,0686	7856,2240	6593,0259	3714,6310	5440,4201	8216,9853	279,2912
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	0,0124	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	0,2530	0,4150	0,2626	0,1619	0,0765	0,2348	0,7890
DTP Variable								
Coefficient	0,0255	-0,2023	0,0737	0,0931	-0,0352	-0,0030	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	-0,3690	-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	4,8350	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

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 $\Delta FP_t = \alpha + \beta \Delta TP_t + \epsilon_t$.

Table 6: Future Prices versus Capitalised Prices: individual asset results

(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	0,9000	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	19,2060	11,5670	14,1260	10,3022	7,7464	3,2140	7,4152	31,7240
Observations	731	731	731	731	731	731	731	679
Intercept								
Coefficient	2,1830	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	5,9280	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	0,97466	0,7703	0,9547	0,8697	0,8087	0,7918	1,0556	0,5835
Standard Error	0,01306	0,0116	0,0108	0,0107	0,0116	0,0102	0,0099	0,0190
t Stat	74,64542	66,3494	88,6132	81,0032	69,8970	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	0,7860	0,7718	1,0363	0,5461
Upper 95%	1,0003	0,7931	0,9758	0,8908	0,8315	0,8118	1,0750	0,6208
ANOVA								
SS	2055328,9972	588997,2164	1566880,7941	696403,7535	293167,2303	62638,9782	630679,4665	947693,5981
MS	2055328,9972	588997,2164	1566880,7941	696403,7535	293167,2303	62638,9782	630679,4665	947693,5981
F	5571,9389	4402,2472	7852,3071	6561,5259	4885,5951	6064,0068	11469,9111	941,6548
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

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 $\Delta FP_t = \alpha + \beta \Delta CP_t + \epsilon_t$.

Table 7: Target Prices versus Capitalised Prices: individual asset results

(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	1,4840	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	197,0290	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	1525452,8006	896220,5008	1170423,2875	804002,8344	381300,1144	85645,5716	405439,6879	1607205,2309
MS	1525452,8006	896220,5008	1170423,2875	804002,8344	381300,1144	85645,5716	405439,6879	1607205,2309
F	38820,4085	68568,4530	65025,7907	39844,8494	49691,4882	48553,2918	39520,4245	1489,3063
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	36,4560	19,7418
Significance F	0,0000	0,0000	0,0000	0,0000	0,0146	0,0006	0,0000	0,0000

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 $\Delta TP_t = \alpha + \beta \Delta CP_t + \epsilon_t$.

5 Conclusion

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

That is at least the case for large capitalisation stocks, as our same considers stocks form the 50 European companies that stayed the longest in the Eurostoxx index, over the past 15 years. If, as Falkenstein (1996) suggests research intensity should be positively related with accuracy, due to a learning effect, and, analogously prediction errors should be inversely related with some market factors like size and liquidity, then accuracy on 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 biases, as suggested by Ottaviani and Sörensen (2006), although, based upon our sub-period analysis, that was during the European crise 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, seem to indicate the overall low accuracy, may result from considerable variety in individual firm accuracy and bias size. Nonetheless, we still observe target prices and capitalised prices are just slightly more accurate predictors of future prices and, if anything, capitalised prices seems to do better.

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

One of the limitations of our analysis is the fact we rely on Bloomberg consensus 12-month market prices that are averages of individual analysts forecasts. It could be, a concrete analyst would perform much better (necessarily others would need to perform worse) at particular time periods and/or for a particular set of companies. 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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Figure A1: Correlograms of our Panel variables

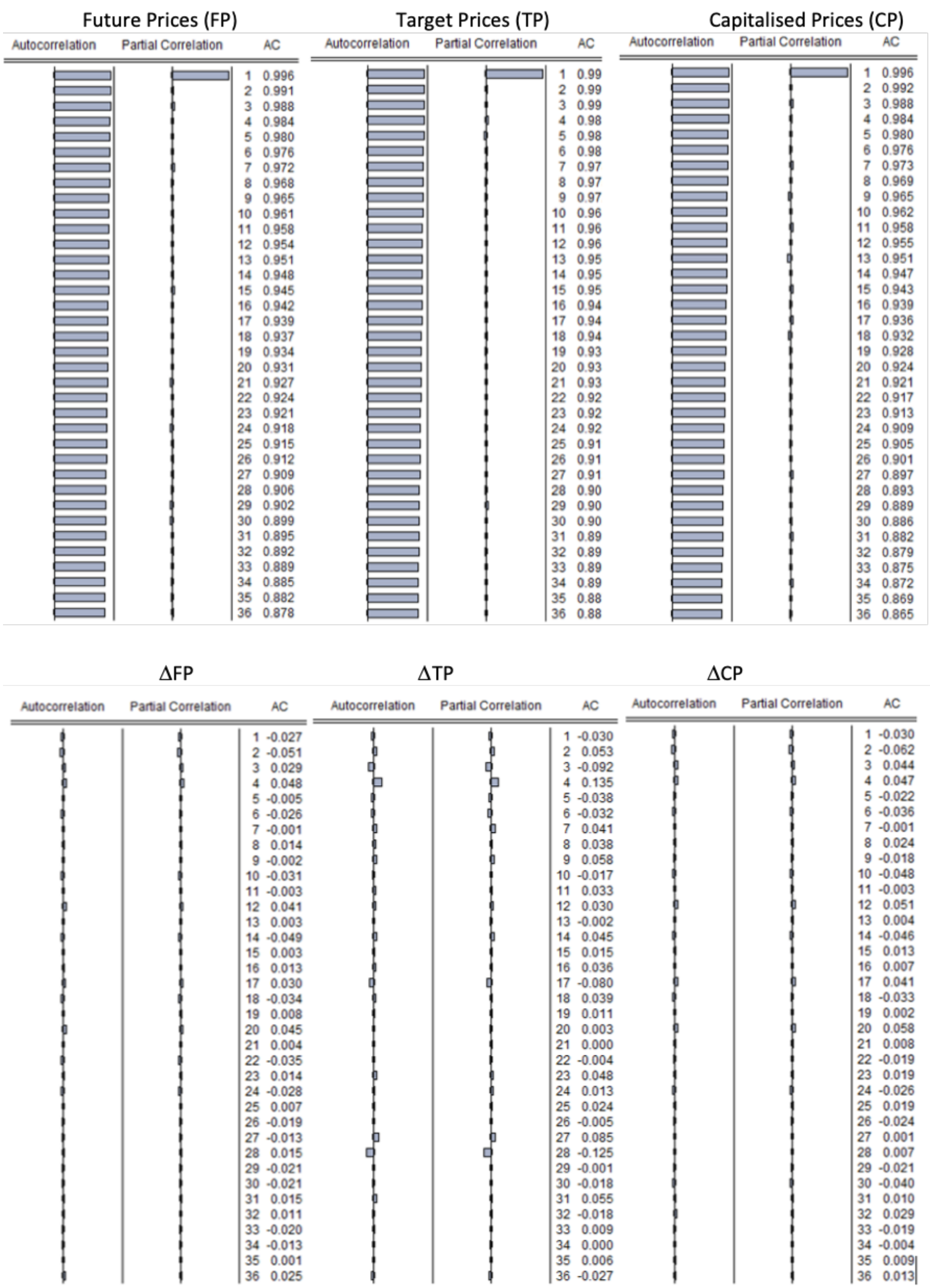


Table A1: Overall Panel Regression: cross fixed effects

	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	0.09	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	-134 690.1	-72 188
F-statistic	3 928.6	2.014	8 007.9	2.588	13 710.0	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 Equation (4)–(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 use the panel data generalization by Bhargava et al. (1982) of the classical Durbin and Watson (1950) statistic.

Table A2: Pre–crise 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 use the panel data generalization by Bhargava et al. (1982) of the classical Durbin and Watson (1950) statistic.

Table A3: Crise 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
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	2298141	28138	1276771	28138	1785249	72490
Log Likelihood	-46064	-21120	-42743	-21120	-44637	-26443
F-statistic	15969	0.003	37781	0.014	70664	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 use the panel data generalization by Bhargava et al. (1982) of the classical Durbin and Watson (1950) statistic.

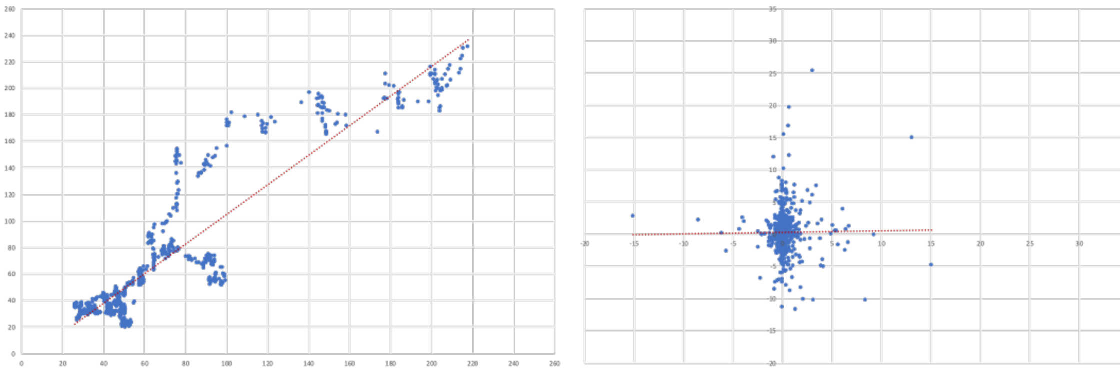
Table A4: Post–crise period Panel Regressions

	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-Statistic	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	3467636	82572	2908700	82567	1047283	12266
Log Likelihood	-67532	-36611	-66082	-36611	-57655	-20927
F-statistic	174790	1.941	211548	2.041	636003	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

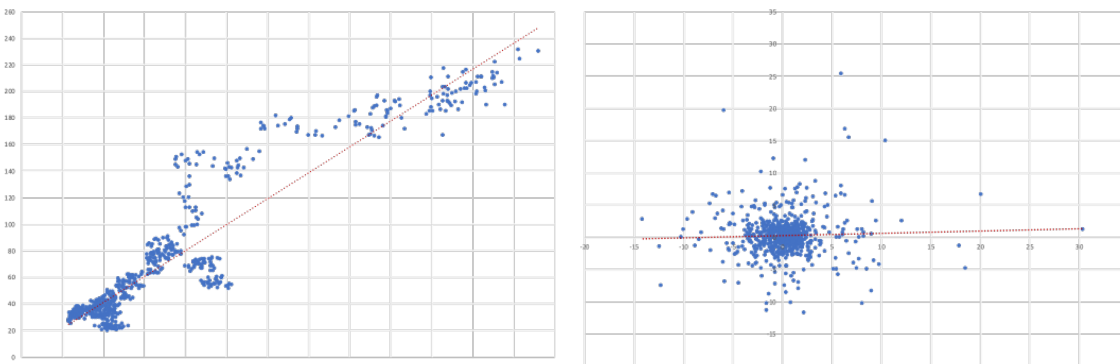
Regression results using panel least squares based upon 16500 balanced panel observations (with a total of 330 periods included and 50 cross-sections). Panel variables are future prices (FP), target prices (TP) and capitalised prices (CP). Each column represents a specific panel regression as in Equationeq:egn. 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 generalization by Bhargava et al. (1982) of the classical Durbin and Watson (1950) statistic.

Figure A2: Addidas

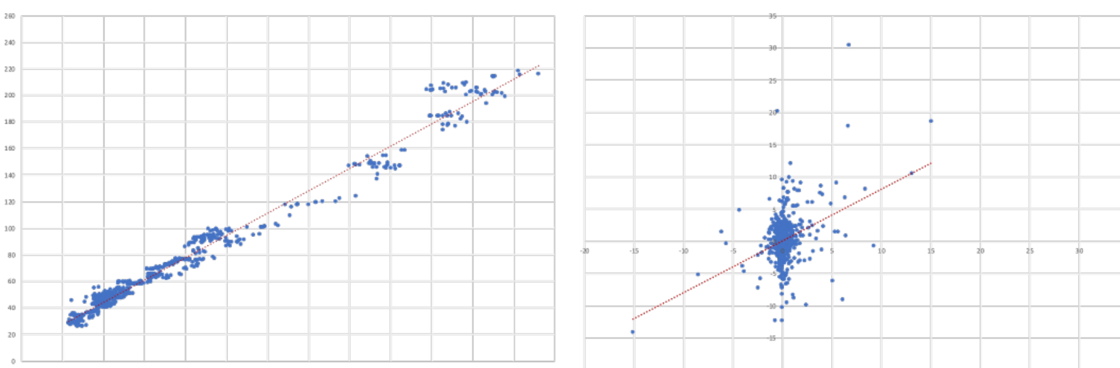
(a) FP vs TP



(b) FP vs CP



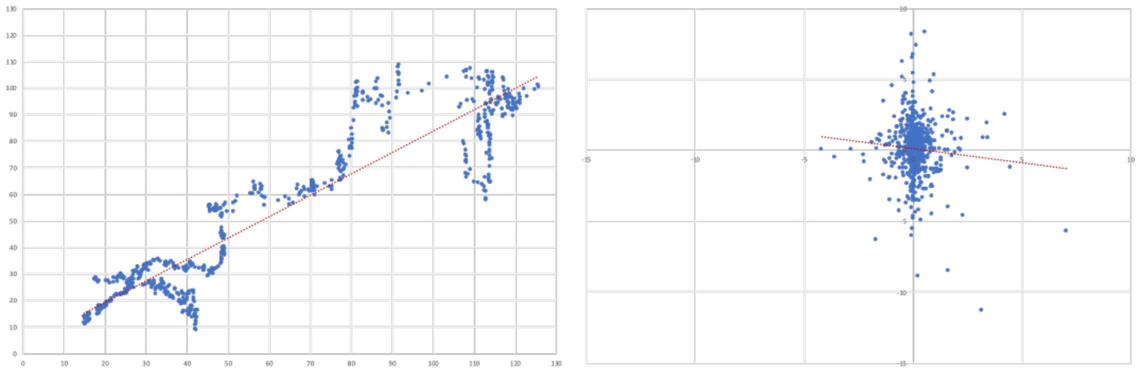
(c) TP vs CP



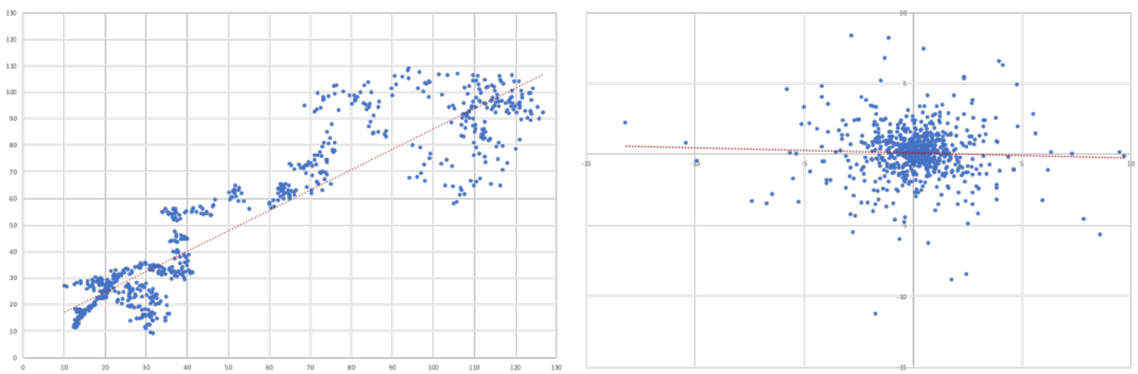
Individual time series regressions using three prices series on Adidas: future prices (FP) ist target prices (TP) capitalised prices (CP) forecasts. On the left-hand-side images of level regressions and on the right-hand-side of regressions in differences.

Figure A3: Anheuser

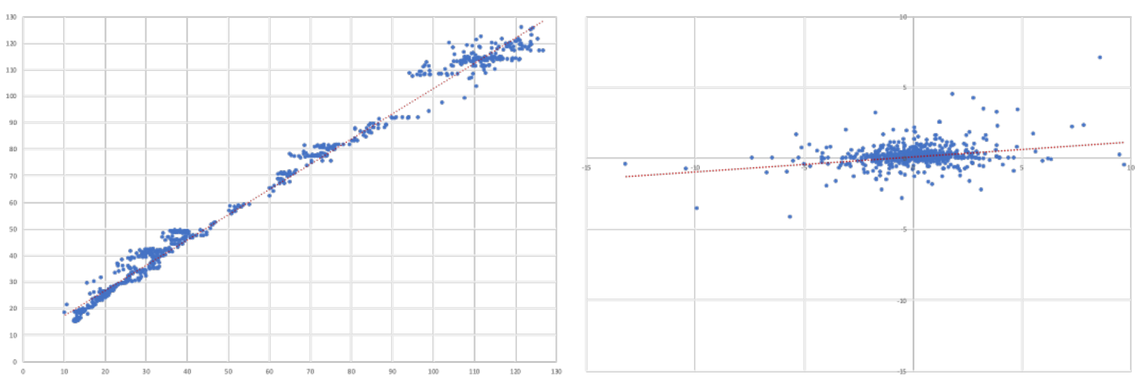
(a) FP vs TP



(b) FP vs CP



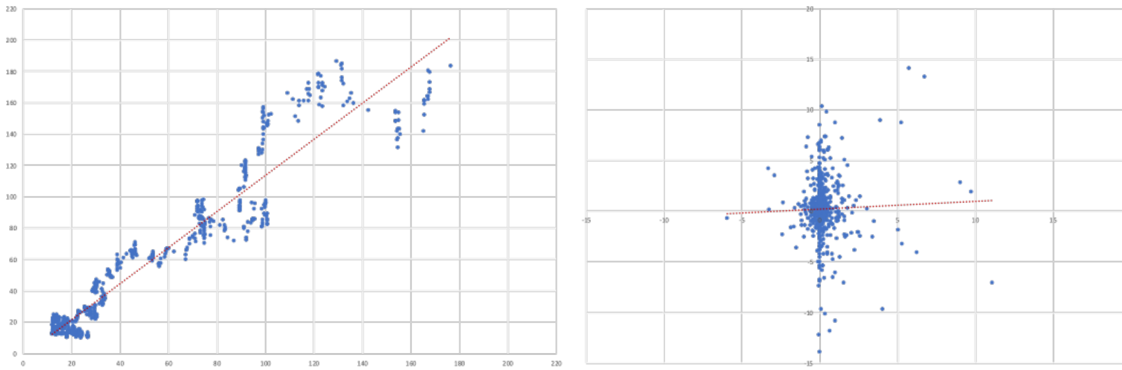
(c) TP vs CP



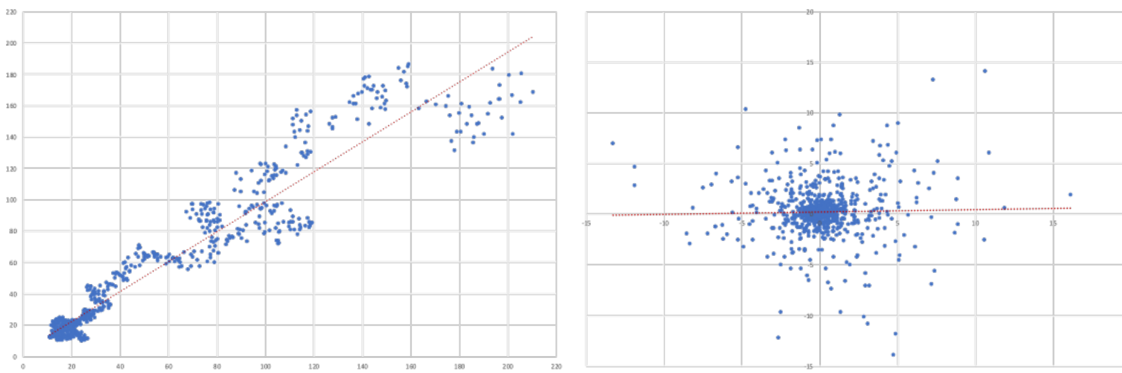
Individual time series regressions using three prices series on Anheuser: future prices (FP) ist target prices (TP) capitalised prices (CP) forecasts. On the left-hand-side images of level regressions and on the right-hand-side of regressions in differences.

Figure A4: ASML

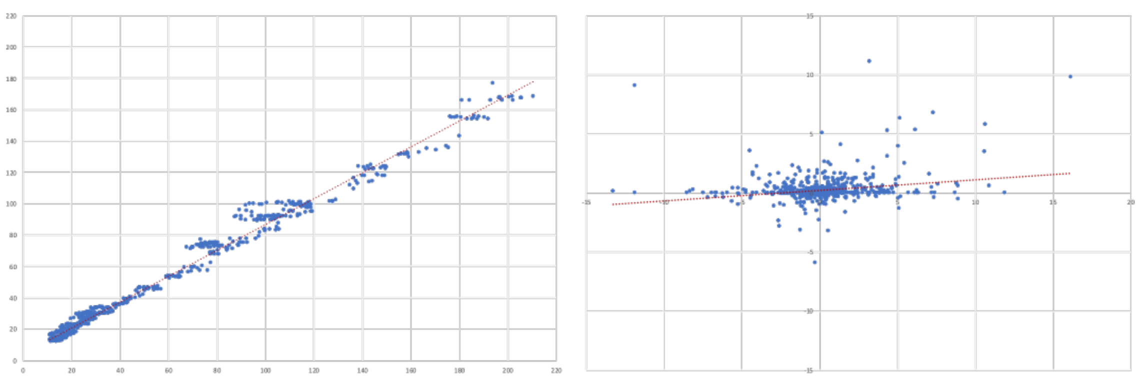
(a) FP vs TP



(b) FP vs CP



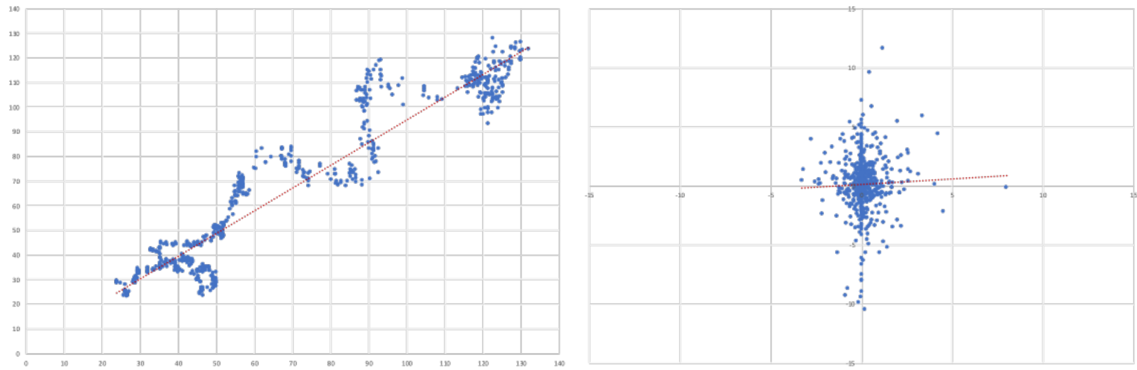
(c) TP vs CP



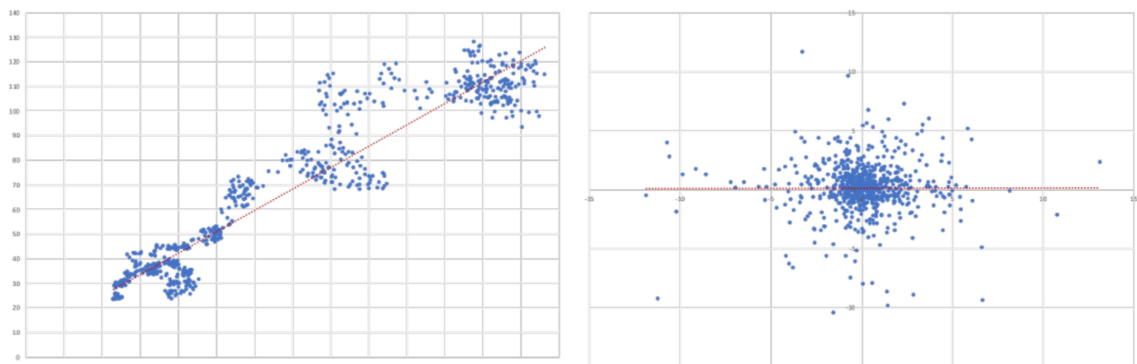
Individual time series regressions using three prices series on ASML: future prices (FP) ist target prices (TP) capitalised prices (CP) forecasts. On the left-hand-side images of level regressions and on the right-hand-side of regressions in differences.

Figure A5: Essilor

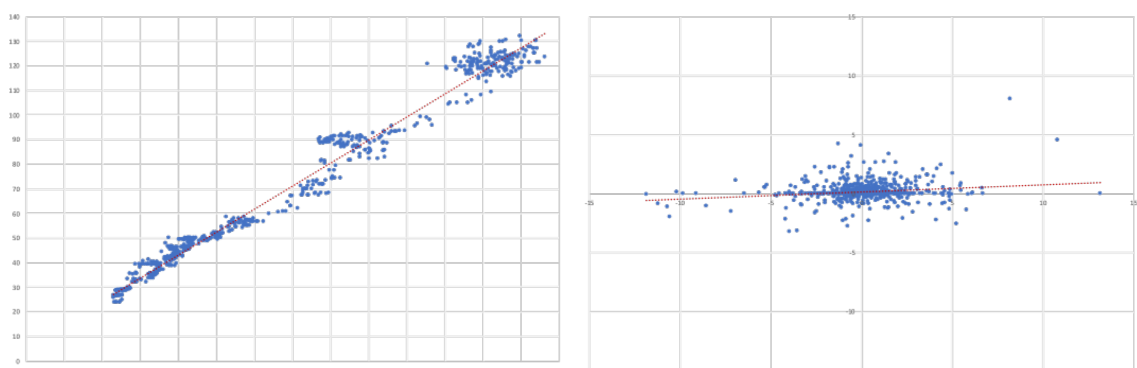
(a) FP vs TP



(b) FP vs CP



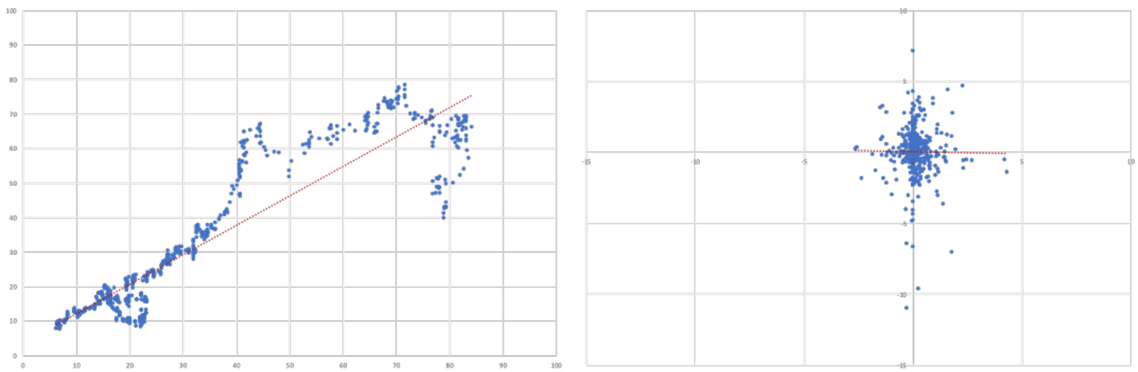
(c) TP vs CP



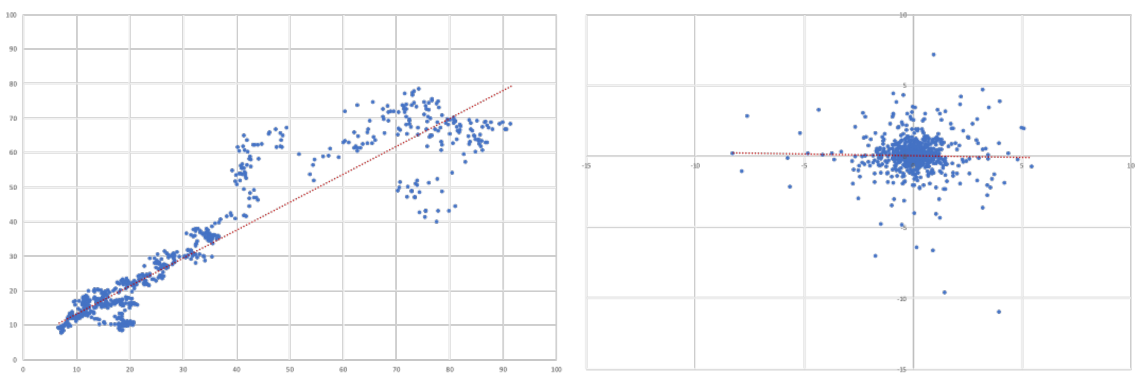
Individual time series regressions using three prices series on Essilor: future prices (FP) ist target prices (TP) capitalised prices (CP) forecasts. On the left-hand-side images of level regressions and on the right-hand-side of regressions in differences.

Figure A6: Fresenius

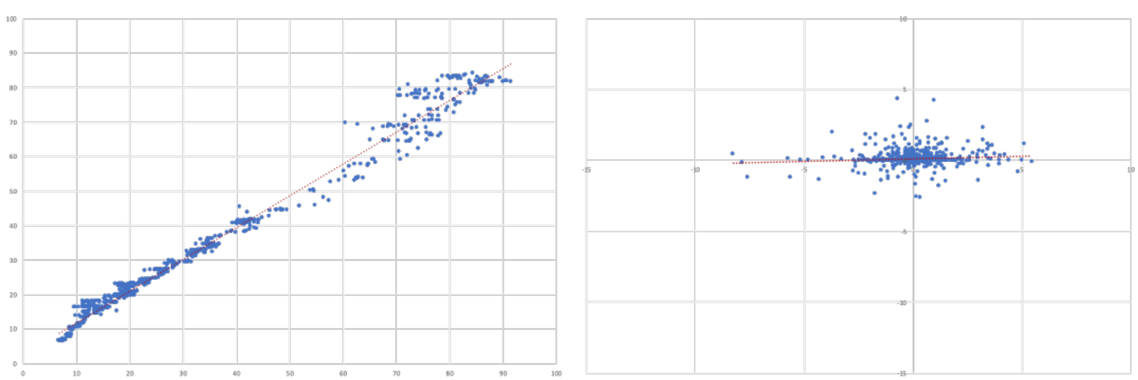
(a) FP vs TP



(b) FP vs CP



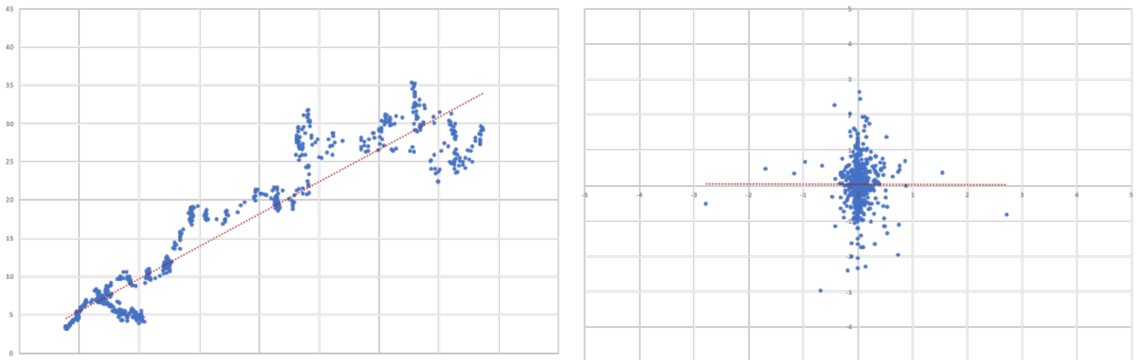
(c) TP vs CP



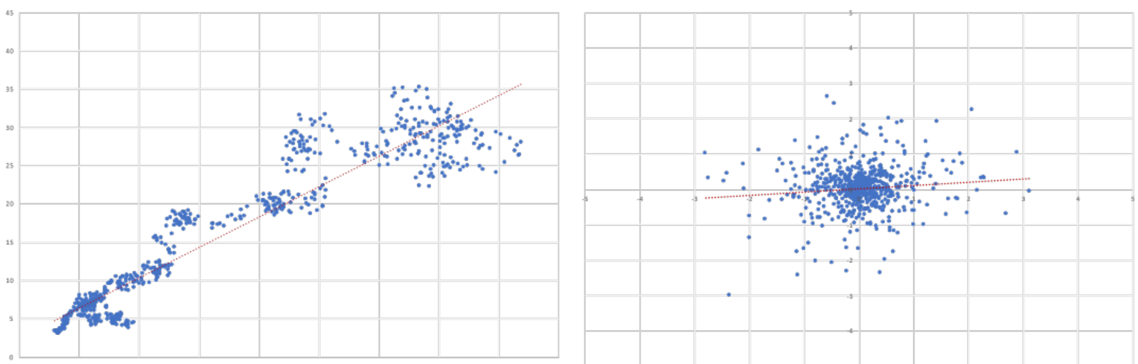
Individual time series regressions using three prices series on Fresenius: future prices (FP) ist target prices (TP) capitalised prices (CP) forecasts. On the left-hand-side images of level regressions and on the right-hand-side of regressions in differences.

Figure A7: Inditex

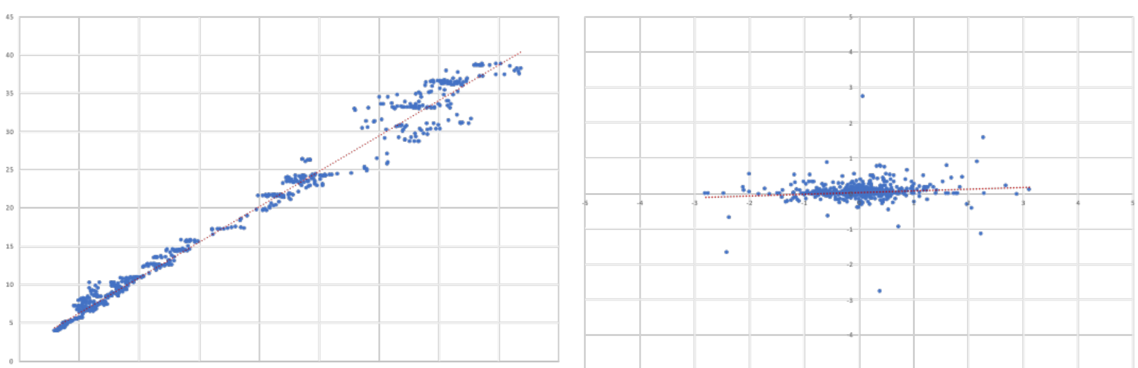
(a) FP vs TP



(b) FP vs CP



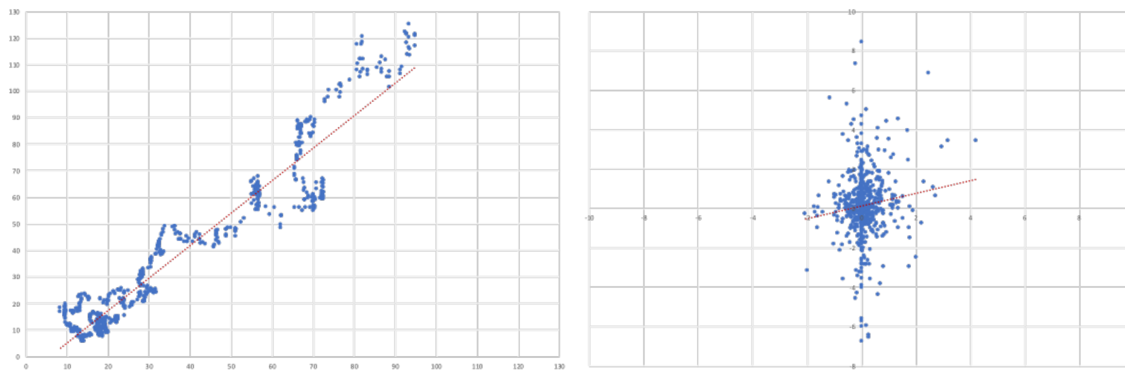
(c) TP vs CP



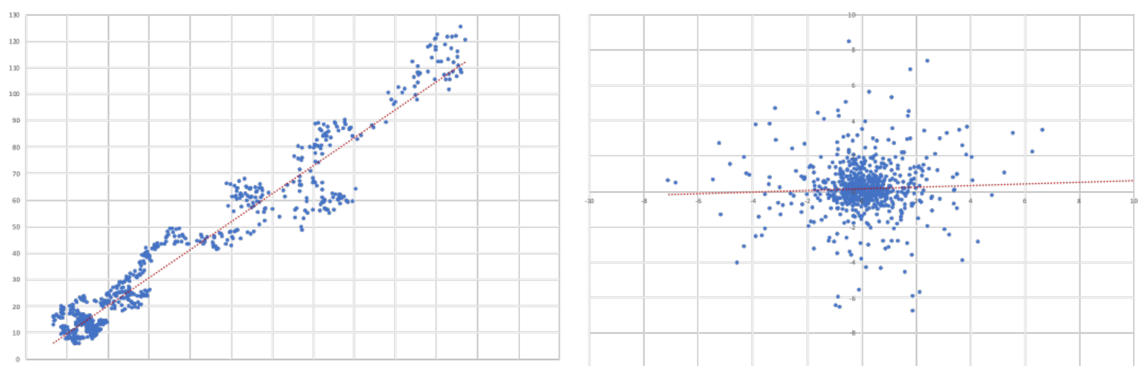
Individual time series regressions using three prices series on Inditex: future prices (FP) ist target prices (TP) capitalised prices (CP) forecasts. On the left-hand-side images of level regressions and on the right-hand-side of regressions in differences.

Figure A8: Safran

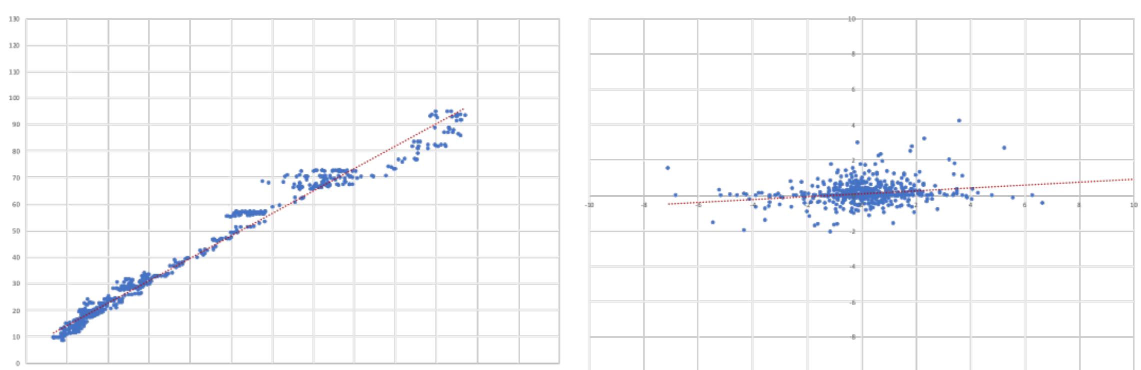
(a) FP vs TP



(b) FP vs CP



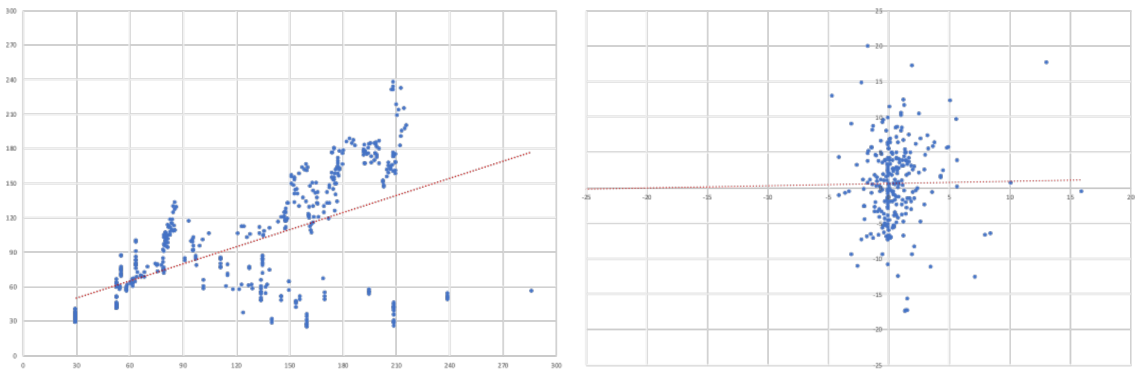
(c) TP vs CP



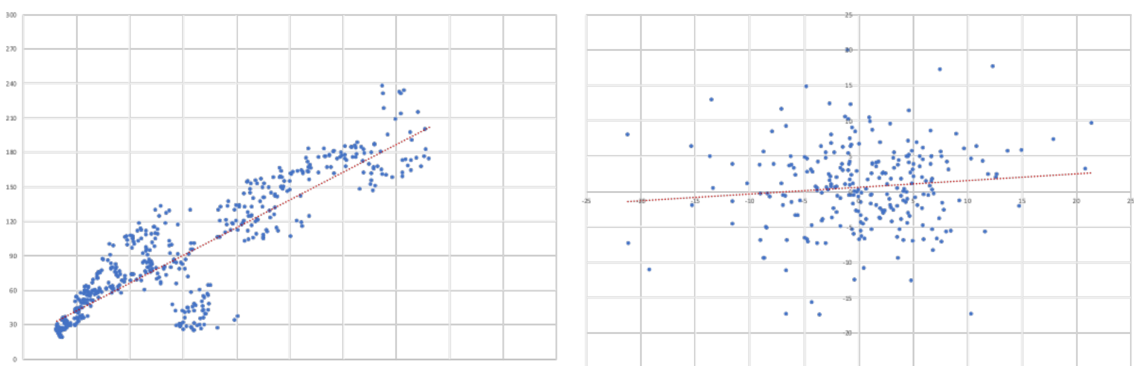
Individual time series regressions using three prices series on Safran: future prices (FP) ist target prices (TP) capitalised prices (CP) forecasts. On the left-hand-side images of level regressions and on the right-hand-side of regressions in differences.

Figure A9: Volkswagen

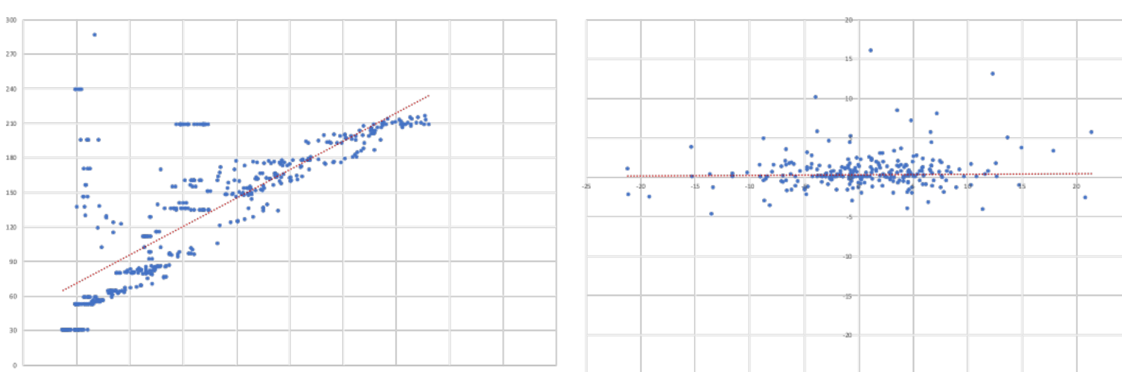
(a) FP vs TP



(b) FP vs CP



(c) TP vs CP



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