Research Article



Equity Analyst Reports and Stock Prices

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Reception date: March 31, 2021 Approval date: October 13, 2021

Abstract: In this paper we carry out cointegration analyses, in order to study whether the relationship between analysts' recommendations and their projected capital gains (or losses), is consistent with the hypothesis that *sell* recommendations are costlier than *buy* recommendations. We find that recommendations that plainly urge the investor to take action (buy, sell) are consistent with their estimated losses. We also find that recommendations react mildly to higher projected losses, and strongly to higher projected capital gains, which is consistent with systematic optimism. Additionally, we could establish that higher projected losses are positively related to dispersion in recommendations. In summary, we got evidence consistent with Womack's (1996) hypothesis that the cost of issuing a sell recommendation is higher than the cost of a buy recommendation.

Keywords: sell-side analysts, intrinsic value, trading incentives, informational value, access to information, financial markets, investment.

JEL Classification: G40, G19, G17, G11, G13

How to Cite

Astaiza Gómez, J. G. & Pérez Pacheco, C. A. (2022). Equity Analyst Reports and Stock Prices. *Apuntes del Cenes*, 41(73). Págs. 43 - 62. https://doi.org/10.19053/01203053.v41.n73.2022.12638

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Informes de renta variable y los precios de las acciones

Resumen

En este trabajo realizamos análisis de cointegración, con el fin de estudiar si la relación entre las recomendaciones de los analistas y sus ganancias (o pérdidas) de capital proyectadas es consistente con la hipótesis de que las recomendaciones de venta son más costosas que las recomendaciones de compra. Encontramos que las recomendaciones que claramente instan al inversionista a tomar medidas (comprar, vender) son consistentes con sus pérdidas estimadas. También encontramos que las recomendaciones reaccionan levemente a mayores pérdidas proyectadas y fuertemente a mayores ganancias de capital proyectadas, lo cual es consistente con optimismo sistemático. Además, hallamos que pérdidas proyectadas más altas están relacionadas positivamente con la dispersión de recomendaciones. En resumen, notamos evidencia consistente con la hipótesis de Womack (1996) de que el costo de emitir una recomendación de venta es mayor que el costo de una recomendación de compra.

Palabras clave: analistas *sell-side*, valor intrínseco, incentivos de trading, valor informacional, acceso a la información , mercados financieros, inversión.

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INTRODUCTION

In order to make profits in the stock market investors and money managers search and interpret information from different sources, including sell-side analysts' valuations. As described in the Occupational Outlook Handbook of the United States Department of Labor, financial analysts evaluate investment opportunities and provide advice or guidance to investors. For instance, as documented by Cheng et al. (2006), "Warfield Associates, Inc. offers a growth fund with total assets of \$161 million. With an investment approach of fundamental (earnings) and bottom-up (focus on companies), the fund places a weight of 80% on research produced by SSAs [analysts], 15% on research by BSAs [buy-side analysts], and 5% on independent research". In particular, sell-side analysts, hereafter named as analysts, work for brokerage firms, and their income is linked to the revenues (commissions) of their brokerage houses.

Although forecast accuracy and reputation are important for analysts (see e.g., Stickel, 1992), different sources of biases in their stock recommendations have been identified in the academic literature. For instance, according to Womack's (1996) hypothesis, an analyst might bias his recommendation because he perceives that the cost of issuing a sell recommendation is higher than the cost of a buy recommendation. More specifically, "sell recommendations can harm a brokerage firm's present and potential investment banking relationships, and thus are discouraged by the firm's investment bankers. Second, top management and investment contacts may limit or cut off the flow of information if an analyst issues unfavorable ratings". Moreover, "optimistic analysts generate more trade for their brokerage firms" (Jackson, 2005). Nevertheless, any of these studies analyze the relationship between analysts' disagreement and projected losses.

In this paper we carry out cointegration analyses, in order to study whether the relationship between recommendations and projected capital gains (or losses), is consistent with the hypothesis that *sell* recommendations are costlier than *buy*

recommendations. If there is no difference in costs or gains between sell. hold and buy recommendations, then the dispersion in analysts' recommendations should have no relationship with the current price or the projected price, since analyst disagreement in recommendations should not be explained by their projected expected loss or gain. Furthermore, the number of cases in which the projected stock price (target price) is positively related to the number of buy recommendations, should be approximately equal to the number of cases in which the target price is negatively related to the number of sell recommendations. Similarly, the number of cases in which the current stock price is negatively related to the number of buy recommendations, should be approximately equal to the number of cases in which the stock price is positively related to the number of sell recommendations (buy cheap, sell high).

We find that analysts' recommendations react stronger for expected capital gains than to expected losses, which is consistent with systematic optimism, and that dispersion in analysts' recommendations is positively related to expected losses, which shows that analyst disagreement has potential value as a piece of information for stock markets. We argue that, as sell recommendations are costlier than buy recommendations, when analysts face the decision of issuing a recommendation for a stock with expected losses, many of them do not reveal their true beliefs by issuing a sell recommendation but react mildly by issuing a hold or a buy recommendation. We can rule out the hypothesis that these findings are consistent with cognitive biases that lead to overvaluation and under-valuation given that we observe strong reactions in one direction only. We can also rule out differences in risks since target prices incorporate this information already.

This research relates to two strands of literature. First, this study is related to the literature upon the usefulness of analysts' reports and, second this research relates to the existing literature on sell-side analysts biases. For practitioners, this paper helps in the understanding of the informational content of analysts' reports found in sophisticated information systems such as Bloomberg.

There are seven sections including the introduction. In section two we show the literature related to market reactions on sell-side analysts and on the information conveyed in analysts' reports. In sections three, four and five, we show our data, variables, and empirical strategies. Finally, in sections six and seven we show our results and conclude.

RELATED LITERATURE

Analysts are important for stock markets as a source of information. In this line, authors such as Malmendier and Shanthikumar (2014), Hilary and Hsu (2013) and Mikhail *et al.* (2007) empirically find that stock returns respond to analysts' forecasts. In addition, Cheng *et al.* (2006) find that equity funds increase the use of analysts' research, relative to buy-side analysts' reports, when their coverage on the stocks held by the fund is higher, or when the average error in their earnings forecasts is smaller, or when the standard deviation of their forecasts is smaller. Furthermore, Li *et al.* (2021) study the dispersion in analysts' target prices and find that it is positively related to future stock risk.

Notwithstanding there is plenty of empirical evidence on stock returns reactions to analysts' reports, the evidence about how useful is the prospective information issued by analysts is far from being conclusive. On the one hand, there is evidence in support of the idea that analysts' recommendations have investment value. Stickel (1992) concludes that his results "suggest that analysts are able to detect the extent to which a stock is overvalued or undervalued": Joos et al. (2016) find that, when an analyst is asked to establish an upper bound and a lower bound to his valuation, the spread between the bounds is associated with firm characteristics that capture the riskiness of shareholder's equity; Womack (1996) finds that new added-to-sell recommendations and new added-to-buy recommendations have a predictive power on stock returns, and Howe, Unlu and Yan (2009) "provide evidence that

changes in aggregate analyst recommendations predict future market and industry returns". On the other hand, Jegadeesh et al. (2004) find that sellside analysts tend to recommend stocks with positive momentum, high growth and high volume, and thus express that "to the extent that their opinion affects public sentiment, this evidence is consistent with the view that they contribute to noise trading in the market". Furthermore, Francis and Soffer (1997) empirically find that investors attach larger weights to the earnings forecast revisions in reports containing buy recommendations.

In addition, the literature also shows that sell-side analysts tend to issue optimistic forecasts. For instance, Easterwood and Nutt (1999) find that analysts overreact to past changes in earnings per share in the upper quartile of the distribution, and that they also underreact to past changes in earnings per share in the lower quartile, which is consistent with systematic optimism. Furthermore, Cowen et al. (2006) and Jackson (2005) show that analysts issue positively biased forecasts in an attempt to increase the trading volume of the stocks they cover, given that their income depends upon the revenues of their brokerage firms. Nevertheless, none of these papers study analysts' disagreement or if analysts are willing to issue clear sell recommendations whenever there are projected capital losses.

DATA AND PRELIMINARY EVIDENCE

In this paper we use data from Bloomberg on publicly listed companies on stock markets. This information includes series of daily prices, consensus analysts' price targets stock price forecast for the next 12 months), number of recommendations, and the number of buy's, hold's and sell's, for 45 firms (stocks) belonging to different sectors of the S&P 500 index from January 1st 2013 to December 31st 2018 (each variable has a total of 70,425 observations) for a total of 422,550 observations. We focus on stocks traded in exchanges of the U.S. since the sell-side analyst profession has been very active in the United States for various years. The sectors (weights in parenthesis) to which the stocks belong correspond to Energy (2.92%), Financials (10.39%), Industrials (8.02%), Consumer Discretionary (10.72%), Consumer Staples (7.03%), Health Care (14.68%), Communication Services (10.94%) and Information Technology (26.82%).

A superficial look at the data provides some suggestive patterns. For instance, in figures 1 and 2 we show the performance and prices of stocks issued by companies engaged in Internet related businesses as those included in the NASDAQ Internet Index (QNET), between the third quarter of 2012 to the fourth quarter of 2016. As we can see in the figures, during this period of more than 4 years, the operating margins and return on capital of firms in this sector showed negative trends which suggest a decrease of the intrinsic values of the stocks issued by companies in this sector. Nevertheless, the stock prices followed a positive trend. This cannot be regarded as a proof of any kind, that intrinsic values are indeed lower to the stock price during this period. according to some absolute measure or valuation model and it is not our attempt in this paper, to draw conclusions on intrinsic values or to obtain a measure of fundamental values. What this does suggest, is that fundamentals did not support the long and permanent raises in stock prices, occurred during four years.

Although it is not our attempt in this paper to explain the causes of this event, research in finance provide some possible explanations on why investors would keep buying stocks issued by companies with poor performances, which include synchronization problems (Abreu & Brunnermeier, 2003), asymmetries of information (Allen et al., 1993; Zhang & Zheng, 2017) and the presence of positive feedback traders (De Long et al., 1990). Interestingly, we also find a similar behavior of firm performance and stock prices at the individual level for Mercado Libre Inc. (Figure 3) and its corresponding American Depositary Receipt (ADR).





Figure 1. QNET Index and Sector Operating Margins. Q32012-Q42016

Source: Bloomberg. The black line represents the QNET Index values, and the red line corresponds to the Operating Margin of the sector as reported by Bloomberg.



Figure 2. QNET Index and Sector Return on Capital. Q32012-Q42016

Source: Bloomberg. The black line represents the QNET Index values, and the red line corresponds to the Return on Capital of the sector as reported by Bloomberg.



Figure 3. Mercado Libre Stock Price and Operating Margins. Q32012-Q42016

Source: Bloomberg. The black line represents the stock price, and the red line corresponds to the operating margin of Mercado Libre as reported by Bloomberg.

We argue that if the costs of issuing sell recommendations were negligible, then analysts sell recommendations based on the firm's performance, should have increased notoriously as stock prices kept rising, taking a different route from the fundamentals of the firm. Meanwhile, the number of buy recommendations should have decreased considerably. But this seems not to be the case. In Figure 4 we show the series of the number of analysts' recommendations for Mercado Libre, from which we can observe not only that the number of buy recommendations (black line) did not decreased notoriously, but also that the number of sell (blue line) recommendations did not increase in a visible and clear manner.

In Figure 5 we show the series of the dispersion in recommendations and also the projected losses (realized stock price minus the projected price, see section Variables) for the American depositary receipt of Mercado Libre, with data from September 30, 2011, to December 21, 2016. The figure suggests that analysts' disagreement in recommendations follow their projected losses.





Figure 4. Recommendations for Mercado Libre Stock. 30/09/2011-12/31/2016

Source: Bloomberg. The black line represents "Buys", the red line "Holds", and the blue line "Sells".



Figure 5. Weekly Series of Recommendations Dispersion and $L_t = p_t - V_t$ Source: Authors' calculations.

When performing a cointegration analysis of the proportion of buy recommendations (P₀, see section 4

for the definition of variables), and the proportion of *sell* recommendations (P_2) , both related to the stock price (p_t) and the analyst price targets (V_t), we can observe, as shown in tables 1 and 2, that analyst recommendations that plainly urge the investor to take action (*buy*, *sell*) are consistent with their estimated losses (gains). The Johansen cointegration tests show that there is only one cointegrating equation for P_0 and one for P_1 relating them to analyst expected losses, and these equations have the following form:

$$P_0 = 0.008596V_t - 0.11723p_t + \omega_{0,t} \quad \text{(buys)}$$

$$P_2 = 0.017704p_t - 0.015059V_t + \omega_{2,t} \quad \text{(sells)}$$

where $\omega_{0,t}$ and $\omega_{2,t}$ follow a stationary process. As V_t exceeds p_t (analyst estimated gains increases) the proportion of *buy* recommendations also augments, and as p_t exceeds V_t (analyst estimated loss increases), the proportion of *sell* recommendations increases.

	P_0 (buy), p_t , V_t		P2 (sell), pt, Vt
Cointegrating Equations	Trace test M. E. Test		Trace test	M. E. Test
None*	0,0009	0,0001	0,0109	0,001
At most one	0,7221	0,7362	0,8373	0,8698
At most two	0,6954	0,6954	0,7131	0,7131

Table 1. Johansen Cointegration Tests. P-values

Source: Authors' calculations. M. E. Test stands for Maximum Eigenvalue Test.

P_0 (buy)	p_t	V _t	Trend	
1,00	-0,11723	0,00860	6,46E-05	
	(0.00193)	(0.00214)	(0.00038)	
P ₂ (Sell)	p_t	V_t	Trend	
1,00	0,01770	-0,01506	0,00061	
	(0.00300)	(0.00330)	(0.00060)	

Table 2. Cointegrating Equations

Source: Authors' calculations. Standard error in parentheses.

Interestingly, as investors keep buying Mercado Libre ADR and its price keep raising during years in which the firm fundamentals deteriorate, analysts opted for issuing less unanimous and less plain spoken recommendations, although their stock valuations imply greater expected losses. As we can see in tables 3 and 4, not only the dispersion (D_t) in recommendations grows as prices move upward from valuations but also the proportion of *hold* recommendations, the neutral recommendation, increases as prices move upward from analyst price targets. This is more easily seen expressing the cointegrating equations in the following form:

$$\begin{split} D_t &= 0.018381 p_t - 0.013625 V_t - 0.001405 t + \omega_{D,t} \quad (dispersion) \\ P_1 &= 0.035527 p_t - 0.020955 V_t - 0.003759 t + \omega_{1,t} \quad (holds) \end{split}$$

where t is a trend variable $\omega_{D,t}$ and $\omega_{1,t}$ both and follow a stationary process. The above equations show that the dispersion in analysts' recommendations as well as the proportion of *hold* recommendations augments as stock prices move upward from analysts' valuations.

	D _t (disper.	sión), p_t, V_t	$P_1(Hold), p_t, V_t$	
Cointegrating Equations	Trace test	M. E. Test	Trace test	M. E. Test
None*	0,0076	0,0008	0,0365	0,0045
At most one	0,7713	0,7585	0,8709	0,8494
At most two	0,7562	0,7562	0,826	0,826

 Table 3. Johansen Cointegration Tests. P-values

Source: Authors' calculations. M. E. Test stands for Maximum Eigenvalue Test.

Dt (dispersion)	p_t	V_t	Trend	
1,00	-0,01838	0,01363	0,00141	
	(0.00314)	(0.00345)	(0.00062)	
P1 (hold)	p_t	V_t	Trend	
1,00	-0,035527	0,020955	0,003759	
	(0.00653)	(0.00731)	(0.0013)	

Table 4. Cointegrating Equations

Source: Authors' calculations. Standard error in parentheses.

Table 5 shows that the target price (V_t) , the stock price (p_t) and the dispersion (D_t) are integrated of order one when using a weekly periodicity. Similar

results in terms of the order of integration were obtained from daily and monthly observations.

Equation	Vt	pt	Dt	P0	P1	P2
Intercept	0,9033	0,3573	0,2635	0,182	0,0783	0,2827
Trend and Intercept	0,7645	0,0555	0,5465	0,3655	0,2074	0,6682
None	0,9162	0,8387	0,8208	0,2395	0,4996	0,4356
Equation	∆Vt	∆pt	∆Dt	$\Delta P0$	∆ P1	∆ P2
Intercept	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000
Trend and Intercept	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000
None	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000

Table 5. Augmented Dickey-Fuller Unit Root Tests in Levels. P-values

Source: Author's calculations. Δ refers to the ADF test over the first difference of the series.

VARIABLES

Let V_t denote the analysts consensus price target at date t and p_t denote the stock price at date t. We define the projected loss estimated by analysts from buying a stock as:

$$L_t = p_t - V_t \tag{1}$$

Intuitively, as the stock price goes higher and the target price goes lower, the projected loss is higher. In order to estimate the level of dispersion in analysts' recommendations, let A be the number of analysts following stock i and let $B_{i,a}$ be a dummy variable that takes the value of one whenever the analyst *a* issued a buy recommendation on stock i. To be more concrete

$$B_{i,a} = \begin{cases} 1 & \text{if the } a - \text{th analyst following stock } i \\ & \text{recommended } Buy \\ 0 & otherwise \\ a = 1, 2, \dots, A \end{cases}$$
[2]

Similarly, define $H_{i,a}$ for *hold* recommendations and $S_{i,a}$ for *sell* recommendations. Therefore, using the variance definition for $B_{i,a}$ we have:

$$Var(B_{i,a}) = E\left[\left(B_{i,a} - E(B_{i,a})\right)^2\right] \quad [3]$$

Since $B_{i,a}$ is a dichotomous variable then $E(B_{i,a}) = P_{i,0}$ where $P_{i,0}$ is the probability that an analyst recommends *buy* for stock i. Therefore, the above expression is:

$$Var(B_{i,a}) = P_{i,0}(1 - P_{i,0})$$
 [4]

Denoting $P_{i,0}$, $P_{i,1}$ and $P_{i,2}$ as the proportion of analysts, at a certain date t = 1, 2, ..., T, whose recommendations were *buy*, *hold* and *sell* respectively, and summing up the variance through recommendations we get a measure for the dispersion in recommendations of stock $D_{i,t}$ (see e.g., Budescu & Budescu, 2012):

$$D_{i,t} = Var(B_{i,a}) + Var(H_{i,a}) + Var(S_{i,a}) = 1 - \sum_{r=0}^{2} P_{i,r,t}^{2}$$
[5]

where $r \in \{0,1,2\}$ denotes the type of recommendation (buy, hold, sell). Notice that, for all i and all t, $D_{i,t}$ is minimal when there exists an r such that $P_{i,r,t} = 1$ and is maximal when $P_{i,0,t} = P_{i,1,t} = P_{i,2,t}$. For instance, in Figure 5 we show the series of dispersion and projected losses for Mecado Libre. As we can see, the level of dispersion during the period shown is larger than 0.3 and smaller than 1, and the projected losses take negative and positive values as the price is greater than the target in some periods and less than the target in others.

EMPIRICAL STRATEGY

We first test the null hypothesis that all the series are non-stationary versus the alternative hypothesis that some of the series are non-stationary, using a t-bar test statistic (IPS test) from a panel data model as in Im et al. (2003). Cointegration tests, as those used in this paper, help to identify whether two or more non-stationary time series are related. Following Im et al. (2003), the model we use to test non-stationarity is

$$\Delta y_{i,t} = \alpha_i + \gamma_i y_{i,t-1} + \sum_{j=1}^{l_i} \rho_{i,j} \, \Delta y_{i,t-j} + \varepsilon_{i,t},$$

$$i = 1, \dots, N \quad t = 1, \dots, T$$
[6]

where $y_{i,t}$ is one of the variables (as described above) for stock *i* at period t, t, $\Delta y_{i,t} = y_{i,t} - y_{i,t-1}$ and $\varepsilon_{i,t}$ is an error term. Thus, we test the following null hypothesis of unit roots

$$H_0: \gamma_i = 0 \quad for \ all \ i$$

against the alternatives

$$\begin{split} H_1: \gamma_i < 0 \quad i = 1, \dots, N_1 \\ \gamma_i = 0 \quad i = N_1 + 1, N_1 + 2 \dots, N \end{split}$$

In addition, we test the null hypothesis that the series are non-stationary versus the alternative hypothesis that the series are stationary, using the test of Levin, Lin and Chu (2002) (LLC test). More precisely, from the model

$$\Delta y_{i,t} = \alpha_i + \delta y_{i,t-1} + \sum_{j=1}^{l_i} \theta_{i,j} \, \Delta y_{i,t-j} + u_{i,t},$$

$$i = 1, \dots, N \quad t = 1, \dots, T$$
[7]

we test

$$H_0: \delta = 0$$

against

$$H_1: \delta < 0$$

Besides the lags and the lags of the first differences, both the IPS and the LLC tests also include time trends.

We check the consistency of stock recommendations which clearly urge for action (buy, sell) by estimating the following cointegrating equations:

$$P_0 = \beta_{0,v} V_t + \beta_{0,p} p_t + \omega_{0,t} \qquad [8]$$

$$P_2 = \beta_{2,p} p_t + \beta_{2,\nu} V_t + \omega_{2,t}$$
 [9]

where $\omega_{0,t}$ and $\omega_{2,t}$ follow a stationary process and P_0 , P_2 , V_t and p_t are defined as above. If analysts' recommendations are consistent with their estimated losses, then $\beta_{0,v} > 0$; $\beta_{0,p} < 0$; $\beta_{2,p} > 0$; $\beta_{2,v} < 0$. After checking for this consistency and following the hypothesis that issuing *sell* recommendations is more costly, we analyze how dispersed are analysts when their estimated loses increase. To do this, we estimate the following cointegrating equations:

$$D_t = \beta_{D,p} p_t + \beta_{D,v} V_t + \omega_{D,t} \quad [10]$$

$$P_1 = \beta_{1,p} p_t + \beta_{1,v} V_t + \omega_{1,t} \quad [11]$$

where $\omega_{D,t}$ and $\omega_{1,t}$ follow a stationary process, and D_t and P_1 are defined as above. We repeat this cointegreation analysis for the 45 stocks in the sample.

RESULTS

We perform panel data unit root tests for each variable as explained in the previous section. The results of the IPS tests, shown in table 6, indicate that most of the series (stocks) are non-stationary. In this same line, the test of LLC applied to each of variable, does not reject the null hypothesis that the series are non-stationary. Since differencing the series results in stationary data, we keep the series in levels for the estimation of parameters in a cointegration framework.

Weekly Observations						
Test	Vt	pt	Dt	P0	P1	P2
Levin, Lin and Chu	0,9997	0,1103	0,6312	0,191	0,1882	0,1078
Im, Pesaran and Shin	1	0,1084	0,3071	0,4383	0,0647	0
Test	ΔVt	∆pt	∆Dt	ΔP0	$\Delta P1$	∆P2
Levin, Lin and Chu	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000
Im, Pesaran and Shin	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000

Table 6. Panel Data Unit Root Test. P-values

Source: Authors' calculations. \$\Delta\$ refers to the Levin, Lin and Chu and the Im, Pesaran and Shin test over the first difference of the series.

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Now we describe the results of the cointegration analyses. For all of the 45 stocks, the trace test of zero cointegrating equations was rejected at the 5% level. In addition, as shown in Table 7, the number of cases in which the projected stock price (target price) is positively related to the number of buy recommendations, is larger than the number of cases in which the target price is negatively related to the number of sell recommendations (88% for positive $\beta_{0,\nu}$ v.s. 73% of negative $\beta_{2,\nu}$), i.e. analysts react mildly to higher projected losses and strongly to higher projected capital gains. This is consistent with the literature showing that analysts exhibit systematic optimism, e.g., Easterwood and Nutt (1999).

Also, the number of cases in which the current stock price is negatively related to the number of buy recommendations (88%), is larger than the number of cases in which the stock price is positively related to the number of sell recommendations (64\%), i.e., analysts again, react mildly to higher projected losses. Moreover, the dispersion in analysts' recommendations has a significant relationship with the current price and the projected price, where higher projected losses are positively related to dispersion in analysts' recommendations: for most stocks in the sample, when the current stock price increases (73% of positive $\beta_{D,p}$) or the target price decreases (74% of negative $\beta_{D,p}$), the dispersion level augments. This result resembles those in Li et al.

(2021), where dispersion in target prices is positively related to future stock risk. Although not directly comparable, our results as well as those in Li *et al.* (2021) tell us that disagreement among analysts is a valuable source of information for stock markets.

Table 7. Percentage of Stocks with

 Positive and Negative Estimates

	<i>β0,p</i>	β0,v	β2,p	β2,v	βD,p	βD,v
Positive Estimates	12%	88%	64%	27%	73%	27%
Negative Estimates	88%	12%	36%	73%	26%	74%

Source: Authors' calculations.

CONCLUSIONS

In this paper we test the hypothesis that *sell* recommendations are costlier than *buy* recommendations by carrying out cointegration analyses and find evidence in favor of it.

We find that analysts' recommendations that plainly urge the investor to take action (buy, sell) are consistent with their estimated losses (gains). That is, as analysts' target prices move upward and stock prices move downward (analyst estimated gain increases), the proportion of *buy* recommendations augments; and as the stock prices raise and target prices fall (analyst estimated loss increases), the proportion of *sell* recommendations increases.

Importantly, we find that analysts' recommendations react mildly to higher projected losses, and strongly to higher

projected capital gains. For our sample, the number of cases in which the target price is positively related to the number of *buy* recommendations, is larger than the number of cases in which the target price is negatively related to the number of *sell* recommendations. In addition, the number of cases in which the current stock price is negatively related to the number of *buy* recommendations, is larger than the number of cases in which the stock price is positively related to the number of *sell* recommendations.

Moreover, we find that higher projected losses are positively related to dispersion in analysts' recommendations. Specifically, the disagreement in analysts' recommendations has a significant relationship with the current price and the projected price: for most stocks in the sample, when the current stock price increases or the target price decreases the dispersion level augments. This exposes that analyst disagreement is an important piece of information for stock markets.

We rule out the hypothesis that these findings are consistent with cognitive biases that lead to overvaluation and under-valuation given that we observe strong reactions in one direction only. We also rule out differences in risks since target prices incorporate this information already. As a specific interesting case, we also use data of Mercado Libre ADR for a period of four years, period in which its operating margins and returns on capital showed a negative trend. While the fundamentals suggested a decrease in the intrinsic value of Mercado Libre. the dispersion in analysts' recommendations as well as the proportion of hold recommendations raised as the stock price moved upward and analysts' valuations downward. If the costs of issuing sell recommendations were negligible, as the price behavior departed from the fundamentals of Mercado Libre, the number of analysts' sell recommendations, based on firm performance, should have increased as stock prices kept rising.

Further research must be done in order to understand how analysts evaluate the prospects of firms during periods of bad performance and what strategic decisions they take with regards to how they reveal their private information. Moreover, in the same line of research of this paper, better establishing the informativeness of dispersion in analyst recommendations relative to recommendations themselves, is important for a test on the profitability of portfolios, build upon analyst disagreement which would provide new insights on how to incorporate analysts' information on investment decisions.

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ACKNOWLEDGMENTS

To the anonymous reviewers of the Journal, for their comments and suggestions.

DECLARATION OF A CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

FUNDING

This research was developed with own resources provided by the authors.

AUTHOR CONTRIBUTIONS

The authors worked together in this article.

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