Deutsche Bank
Markets Research

North America
United States

Quantitative Strategy
The Quant View

Date
4 March 2014

Sheng Wang
sheng.wang@db.com

Miguel-A Alvarez
miguel-a.alvarez@db.com

Javed Jussa
javed.jussa@db.com

Zongye Chen
john.chen@db.com

Allen Wang
allen-y.wang@db.com

Yin Luo, CFA
yin.luo@db.com

North America: +1 212 250 8983
Europe: +44 20 754 71684
Asia: +852 2203 6990

The wisdom of crowds: crowdsourcing earnings estimates

Quantitative macro and micro forecasts for the month
In this report we present our latest quantitative forecasts for the coming month. Our models are designed to generate both bottom-up stock selection ideas as well as top-down asset, country, and style allocation calls.

Introducing the crowdsourcing dataset Estimize
Estimize is an online community that allows different types of investors to contribute their financial forecasts. The contributors include the buy side investment professionals, individual traders, independent researchers and students. The merit of the Estimize dataset is based on the diverse group of contributors and the wisdom of the crowd.

More accurate short-term earnings estimates
Our initial findings show that the more timely Estimize forecasts provide greater short-term accuracy when compared to IBES, while IBES estimates do a better job for longer-term forecasts. Specifically, we find Estimize is more accurate than IBES for estimates taken one-week before the announcement date, while the sell-side estimates from IBES show greater accuracy for estimates collected one-month prior to announcement.

Post earnings drift and a corresponding trading strategy
We find that the timelier Estimize forecasts can more accurately identify earnings surprise which results in a greater capture of the post earnings drift. We use this finding to construct a daily trading strategy that goes long the stocks that beat the Estimize consensus and short the stocks that miss.

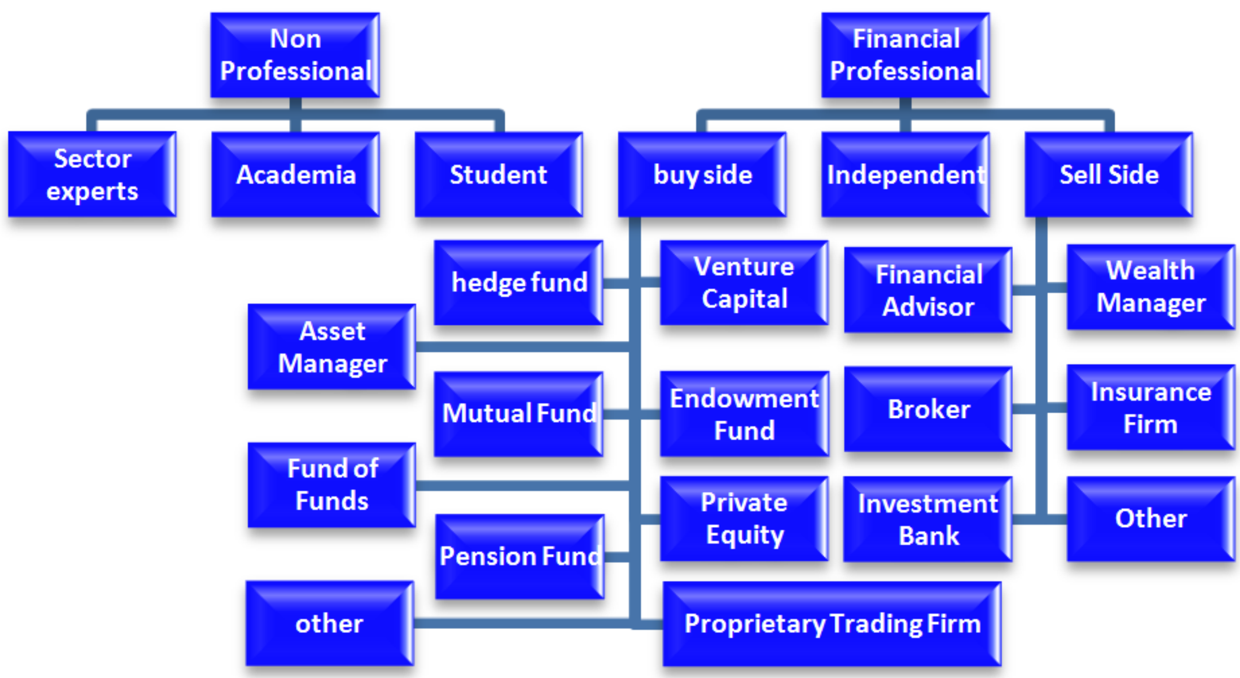
Crowdsourcing earnings estimates

Introducing the Estimize dataset

Earnings estimates are one of the most widely used financial metrics. They are a measure of expected company performance and play an important role in many equity investors' stock selection strategies. Traditionally, earnings estimates are gathered from sell-side analysts at institutional brokers and independent research firms. Data vendors such as Institutional Brokers' Estimate System (IBES) aggregate these estimates and offer daily or monthly updates as well as historical datasets. While there are many data vendors that aggregate sell-side earnings estimates, we have yet to find a reputable database that collects estimates from buy-side analysts and other types of investors.

In this report, we analyze a new database from the crowdsourced community Estimize that collects earnings and revenue forecasts from various different types of investors. It was established in 2011 and has grown rapidly to cover more than 900 US stocks. What sets it apart is that the community of contributors is varied, ranging across buy-side investment professions, individual traders, independent researchers and students. Figure 1 shows the types of the contributors to the database.

Figure 1: Constituents of the contributors of Estimize

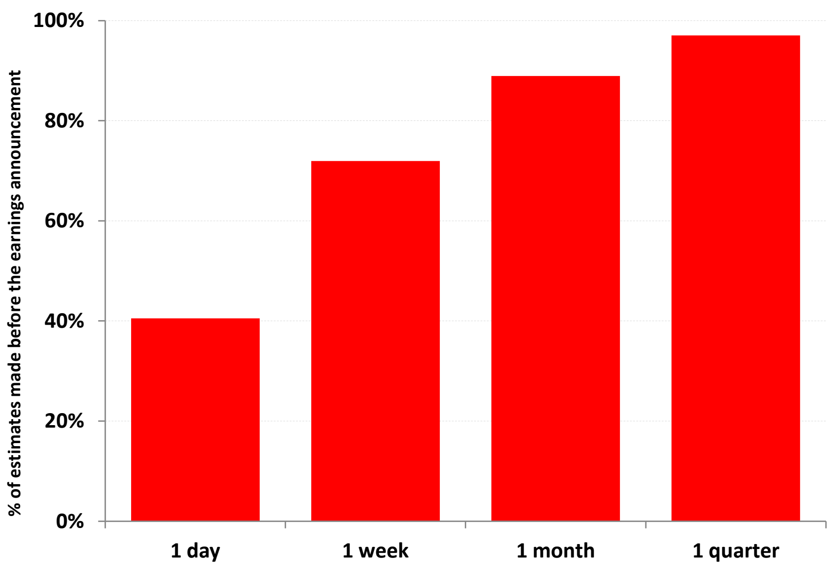


Source: Estimize, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Estimize allows individuals to contribute their estimates anonymously. The underlying concept of the community is to capture the "wisdom of the crowds" in order to reflect investor sentiment and more timely and accurate earnings forecasts. The data structure consists of two main parts: estimates and contributors. The estimates are made up of EPS and revenue forecasts across each individual contributor. The data includes the contributor's unique ID, a timestamp for which the estimates were created and the corresponding fiscal quarter of the forecasts. Most estimates cover the current quarter (FQ1), but the platform allows for estimates up to the fourth fiscal quarter (FQ4). Each contributor is assigned a unique ID which makes it possible to track the accuracy for each individual.

Figure 2 shows the percentage of estimates made within one day, one week (including the first day), one month and one quarter before the earnings announcement. The chart shows that 40% of the estimates are made within 24 hours of the announcement, and the majority of the estimates are made within one week. Few estimates are made a quarter earlier. This is quite different from IBES, where most of the estimates are entered at least one-month in advance, lending itself more useful to longer horizon investors.

Figure 2: Percentage of estimates made before the earnings announcement



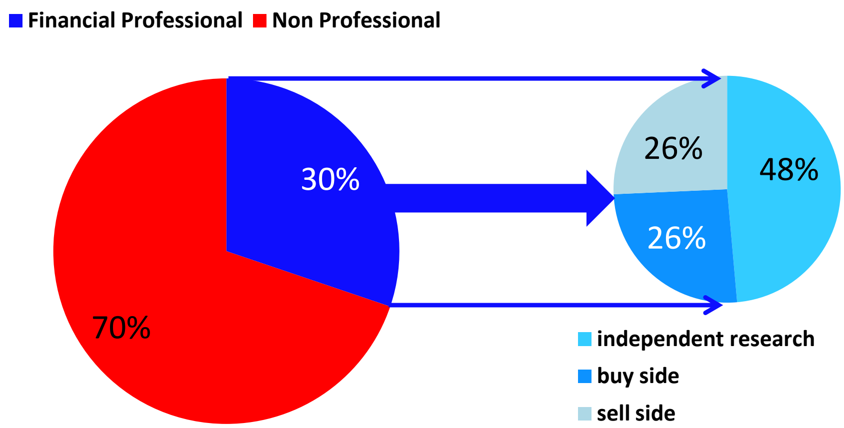
Source: Estimize, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Who's contributing?

Figure 3 shows that more than two-thirds of the estimates are collected from non financial professionals. Among the financial professionals, half are independent researchers and the other half are split evenly between buy-side and sell-side analysts.

The sample data shows that the data covers a diverse range of investors and the information should be complementary to the traditional institutional data sources such as IBES.

Figure 3: Component of the Estimize contributors



Source: Estimize, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

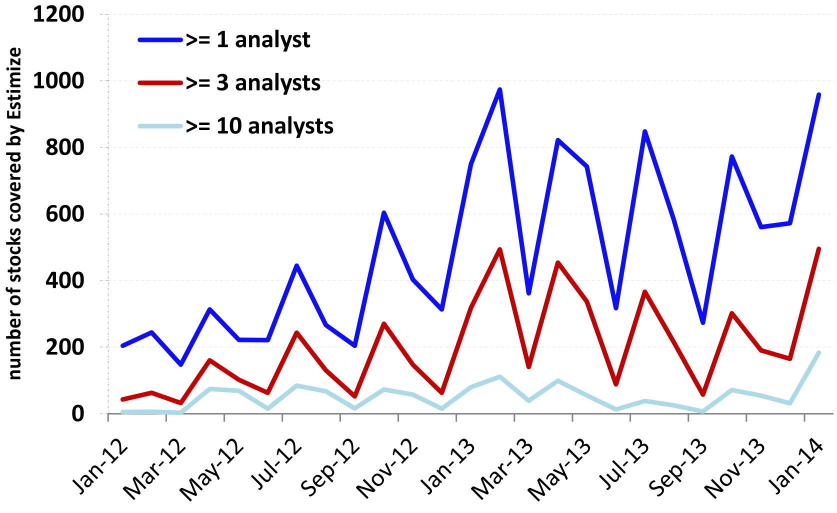
Unfortunately, as is the case with many of the newer and unique data sources, the history of the Estimize dataset is relatively short and coverage is less extensive than that of traditional sell-side estimate databases such as IBES.

In this report, we focus in most part on the EPS estimates from Estimize and begin our analysis in 2012 since much of the data prior to that is too sparse.

Figure 4 shows the number of stocks covered in the Estimize database that are members of the Russell 3000 universe. Coverage is defined by the number of unique tickers which have at least one estimate on some day in a current fiscal quarter during that month; regardless of whether or not the company reports during that month.

We find a strong seasonal component in the data due to earnings seasons and the fact that most estimates are not contributed until one week before the actual announcement (Figure 2). In addition, stock coverage drops quickly as we increase the number of required contributors.

Figure 4: Estimize coverage on the Russell 3000 universe

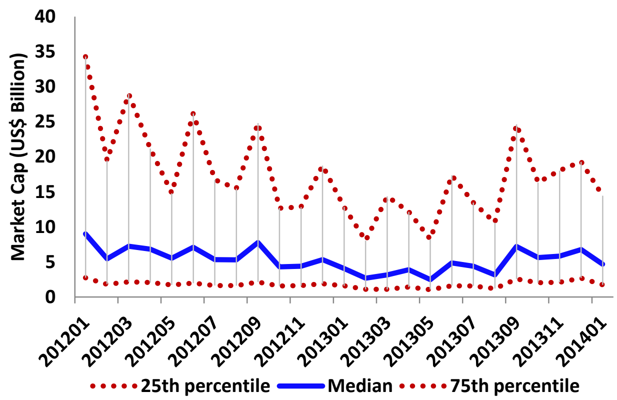


Source: Estimize, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 5 shows the median, 25th percentile, and 75th percentile of the market cap covered by Estimize over time. The coverage consists mainly of large and midcap US stocks and the distribution of market cap shows to be steady over the sample.

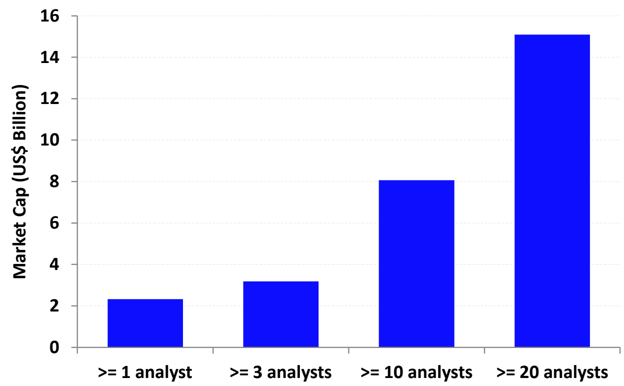
Figure 6 shows the median market cap of the stocks covered by Estimize across different numbers of contributor (analyst) coverage. As expected, we find that larger cap stocks which demand more attention are covered by a larger number of contributors. This is consistent with the traditional institutional databases in that larger cap companies will have more analyst coverage.

Figure 5: Market Cap of stocks covered by Estimize (US$ Billion)



Source: Estimize, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 6: Median Market Cap of stocks covered by Estimize across different analyst coverage (US$ Billion)



Source: Estimize, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

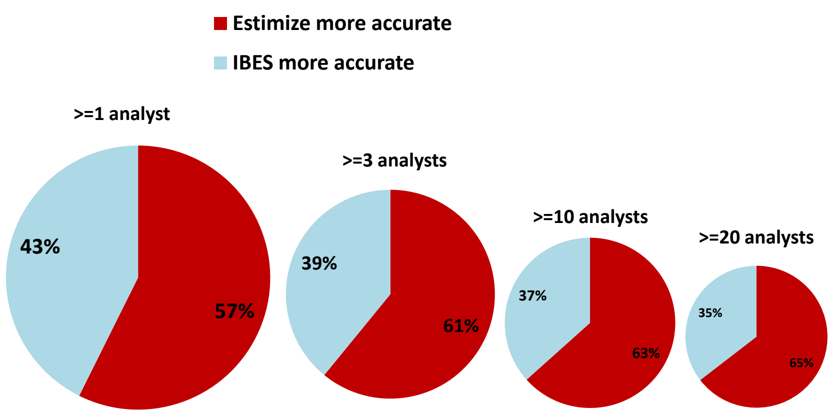
Gauging the accuracy of crowdsourcing?

Comparing estimates

The first question we must address is how it compares to traditional sell-side estimate data covered by vendors such as IBES. Can it add value beyond these long existing sell side analyst forecasts?

To get a sense of the accuracy, we compare the last Estimize EPS forecasts with those from the daily IBES database for stocks that are available in both datasets. We begin by comparing the average EPS estimates in each database with actual EPS reported on the announcement date. Figure 7 shows that over the sample, the average estimate across the Estimize database was closer to the reported number when compared to the IBES average estimate. In addition, as the Estimize coverage increases, the forecast accuracy relative to IBES also increases. EPS estimates for stocks with greater than 20 analysts covering them in Estimize are more accurate 2/3 of the time.

Figure 7: Estimize EPS estimates all estimates vs. IBES

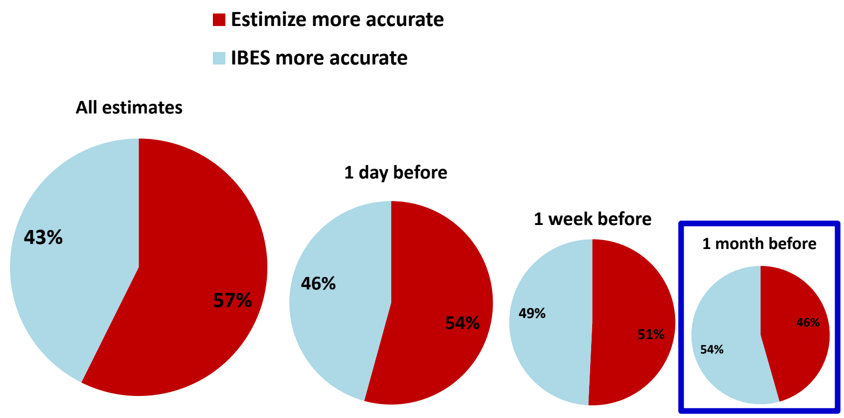


Source: Estimize, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

However, the greater accuracy of Estimize database is in most part due to its timely updating. Recall that most Estimize estimates are entered a few days prior to the earnings announcement (Figure 2), while most IBES estimates are entered several weeks in advance. For a more apples-to-apples comparison, we compare the estimates at different horizons.

Figure 8 shows the accuracy of the average estimates at various windows before the announcement date. The results show that one week before announcement the accuracy across Estimize and IBES is similar. However, when looking at a one-month window, IBES estimates tend to be more accurate than those in Estimize. This suggest that sell-side analysts do a better job at predicting earnings over a longer window while the more timely Estimize data tends to be more accurate within one week of the announcement.

Figure 8: Estimize EPS estimates vs. IBES for longer windows



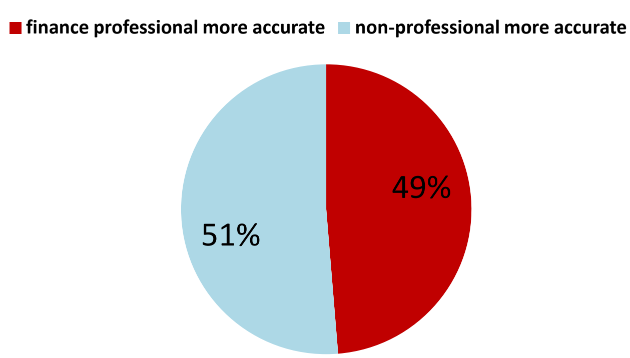
Source: Estimize, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Professionals vs. non professionals

We further compare the EPS prediction accuracy of finance professionals with non-professionals to see if the professionals make more accurate predictions. To our surprise, the data shows that finance professionals slightly underperform non-professionals (see Figure 9); albeit the difference is too small to make any significant or sweeping conclusions. One explanation may be that it is due to selection bias in the Estimize database – i.e. the more accurate professionals do not contribute their estimates to the database.

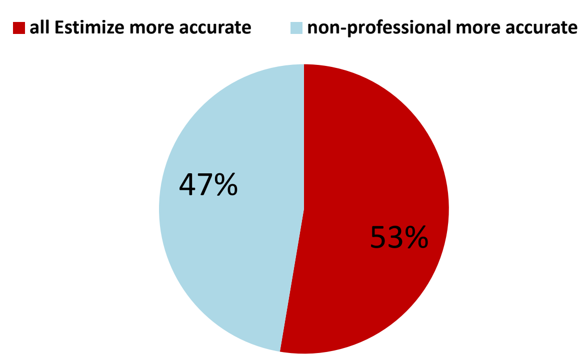
We can also compare the accuracy of the estimates from non-professionals to those of the combination of professionals and non-professionals (see Figure 10). The results show that there is kind of diversification effect in that combining the two actually results in better accuracy than any of two individually.

Figure 9: Finance professional vs non-professional



Source: Estimize, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 10: Non-professional vs. all Estimize estimates

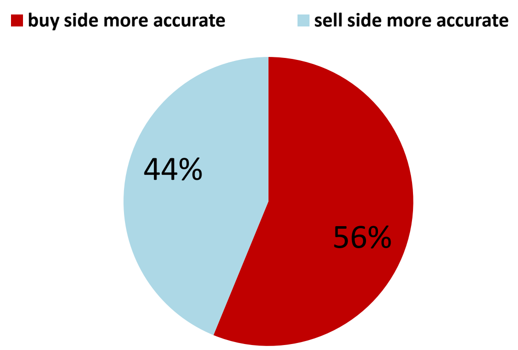


Source: Estimize, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Buy-side vs. sell-side

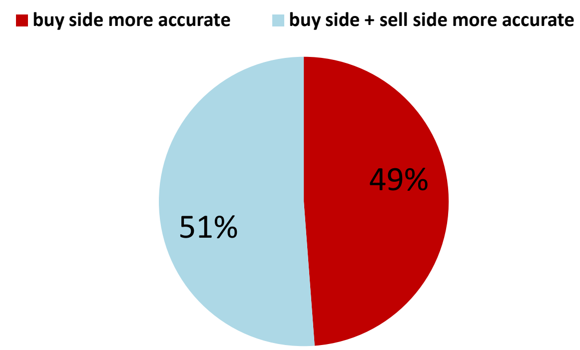
Recall there is approximately the same number of estimates from buy-side and sell-side professionals in the Estimize database (see Figure 3). We next investigate whether there is a significant difference between these two categories in the database. Figure 11 shows that average estimates for buy-side professions are more accurate than those from the sell-side in the Estimize dataset. However, due to the limited sample size in the Estimize buy side and sell side estimates (Estimize started to label the buy side and sell side estimates start in 2013), it may not be statistically significant to make a definite conclusion. Similar to the results from professionals versus non-professionals above, this result could be due to selection bias in that the more accurate sell-side analysts are not contributing their estimates to the database. Nonetheless, Figure 12 shows that combining the sell-side and buy-side estimates actually increases accuracy suggesting a sort of diversification benefit from including both types of professionals in the Estimize database.

Figure 11: Comparing buy side and sell side in Estimize



Source: Estimize, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

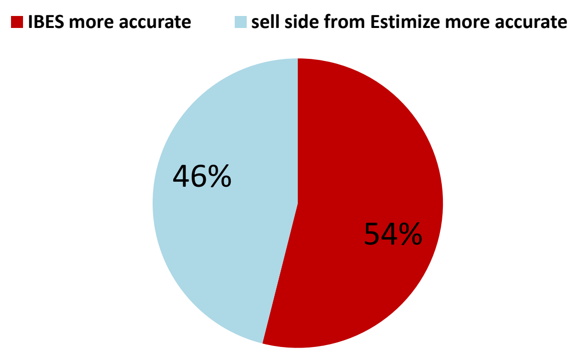
Figure 12: Sell side add value to buy side estimates



Source: Estimize, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

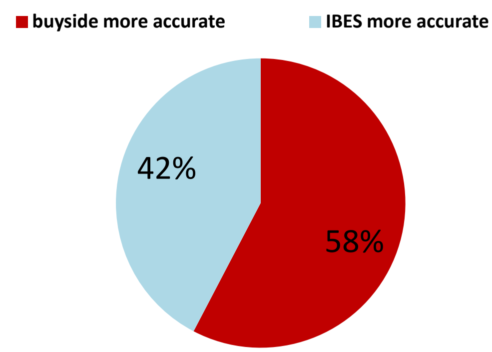
Figure 13 further compares the difference between Estimize sell side and the IBES sell side. The results show that IBES sell-side estimates are more accurate than those from Estimize, which lends some credence to our hypothesis that Estimize sell-side data may have a level of selection bias. In Figure 14, the performance for IBES sell side compared with buy side estimates are similar as the sell side compared with buy side in Figure 11. This is as we expected, since IBES are mostly sell side analysts estimates, so they should have some similarity with the sell side estimates from Estimize.

Figure 13: IBES compared with sell side from Estimize



Source: Estimize, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 14: IBES compared with buy side from Estimize



Source: Estimize, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

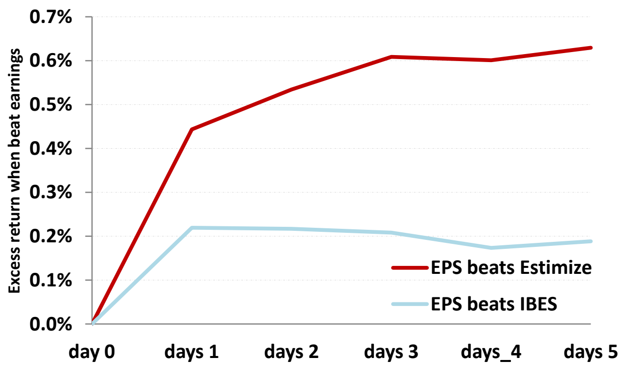
Post earnings announcement surprise

Post earnings drift is the return following an earnings announcement that is attributable to surprise. Typically, companies who beat earnings consensus tend to outperform the market over subsequent trading while stocks that miss expectations tend to underperform the market.

To analyze the post earnings drift in both the IBES and Estimize datasets we use an event study. The day one return of the post earnings announcement is calculated using the open to close price if the earnings was announce before the market opens; and use next day open to close if the earnings was announce after the market close. The following day's returns are all calculated using close to close price returns. The S&P 500 total return index is used as the market return

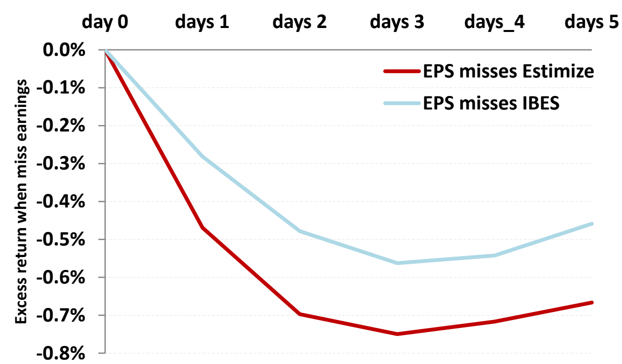
Figure 15 and Figure 16 show the average excess return to the market for earnings surprises greater than 10% for both Estimize and IBES estimates. In both cases the more timely Estimize estimates shows bigger post announcement drift for both beats and misses. However, in both cases, the cumulative excess return flattens out quickly after the a few days, due to market efficiency.

Figure 15: Cumulative excess return when estimates beat earnings by more over 10%



Source: Estimize, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 16: Cumulative excess return when estimates miss earnings by more than 10%



Source: Estimize, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

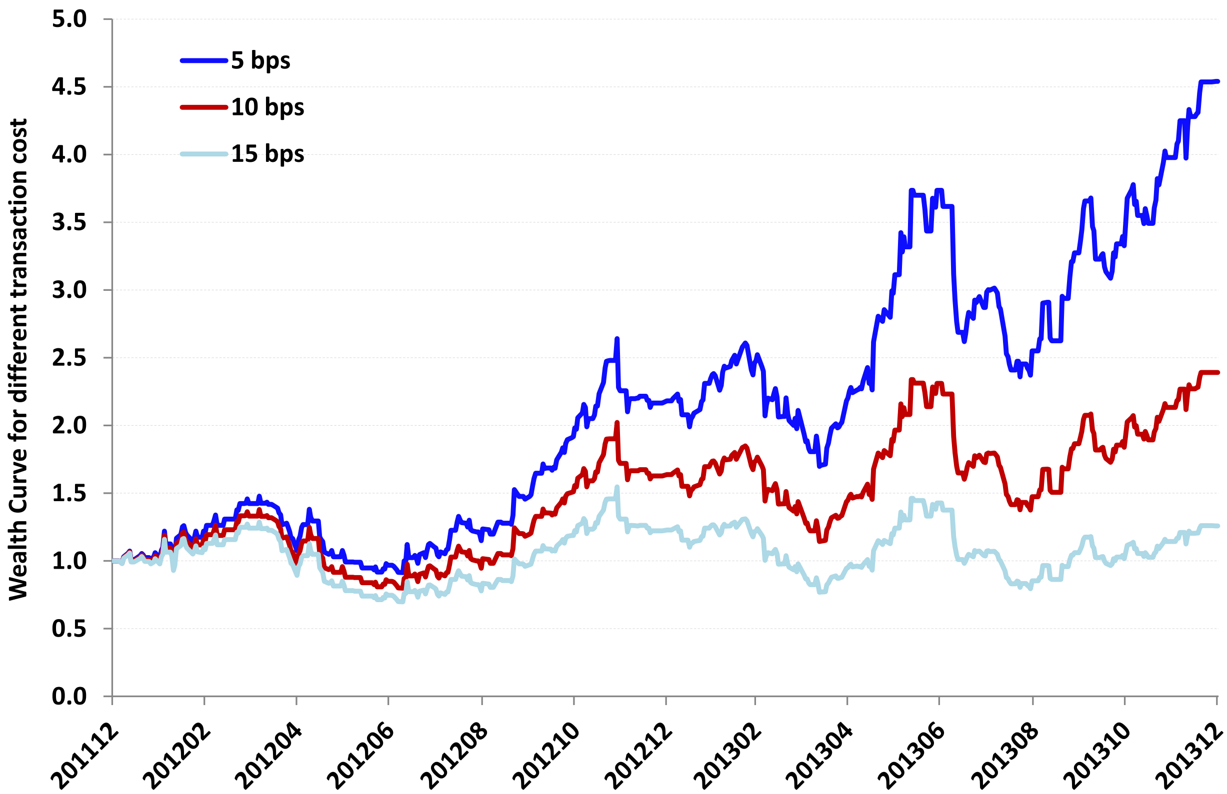
Portfolios based on more accurate earnings estimates

Based on the event study from previous session, we would like to examine the performance of a portfolio based on the same logic: long stocks that beat consensus and short the stocks that miss.

As we already saw in Figure 15 and Figure 16, the earnings drift occurs mostly during the first day of trading after the announcement. For simplicity and illustrative purposes, we construct this portfolio with a one-day holding period, using the open price to close price (because the earnings announcements almost always occurs after the market close). We use SP 500 to hedge when there is no holding in one of the two legs. We call this the Estimize earnings surprise strategy.

Turnover for this strategy is high because the portfolio changes nearly every time it is traded. Figure 17 shows the wealth curve for this strategy under different levels of transaction cost. Naturally, the performance drops quickly as we increase transaction costs. However, even when transaction costs are 15 bps, the net performance is still attractive.

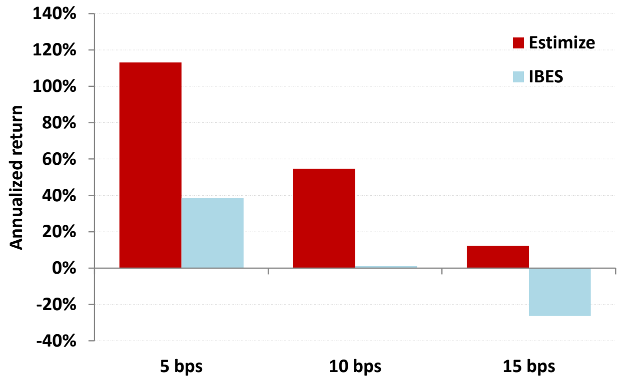
Figure 17: Wealth curve for different transaction cost of the Estimize earnings surprise strategy



Source: Estimize, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

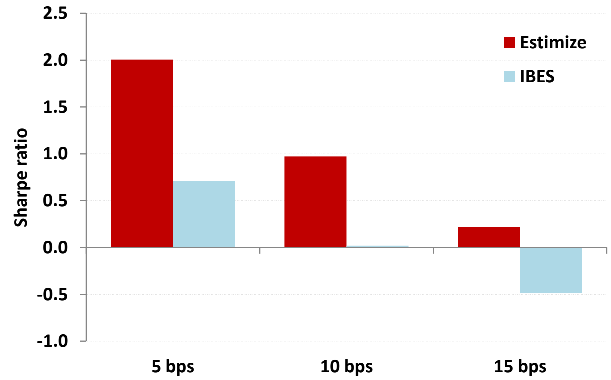
We compared the same strategy based on the same earnings surprise measure using the IBES estimates. Figure 18 show the annualized returns and Figure 19 shows the Sharpe ratio of the two strategies under different transaction costs. For both strategies, the performance decreases quickly as transaction costs increase. When transaction cost increases to 10 bps per trade, the performance of the IBES earning surprise strategy is nearly zero, and it turns negative once we have t-costs increased to 15bps. In contrast, the Estimize earnings surprise strategy, shows an annualized return of 12% under the 15bps t-cost scenario.

Figure 18: Annualized return for the earnings surprise strategy for Estimize and IBES with different cost



Source: Estimize, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 19: Sharpe ratio for the earnings surprise strategy for Estimize and IBES with different cost



Source: Estimize, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

In conclusion we found multiple benefits to using the Estimize dataset; especially in the case of short-term applications in which accuracy is essential. Another interesting byproduct of the analysis was the power of crowdsourcing. We found that some of the value-added in the Estimize dataset was due to the "wisdom of crowds" effect as more predictions give way to greater accuracy. Moreover, the diversity of the contributors provides a greater spectrum of information which can potentially improve investment strategies based on estimates.

We should also be aware of the potential issues with the Estimize dataset. The main issue rests on the thin coverage and the short-term nature of the forecasts; especially when compared to commonly used sell-side estimates data. Also, the short history will pose a problem when trying to analyze the data across different market and economic environments.

Please contact us DBEQS.Americas@db.com for more details of the Estimize dataset.