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CROWDSOURCING EARNINGS AND REVENUE ESTIMATES

More Accurate and Timelier Estimates Lead to Better Investment Strategies

- **Alternative Big Data on Earnings and Revenue Estimate.** Traditionally, investors rely primarily on the sell-side consensus for earnings and revenue forecasts. In this research, we study an alternative data source based on the concept of crowdsourcing. Estimote is an online platform that allows individuals with different backgrounds to contribute their financial forecast. We find Estimote estimates to be not only more accurate and timelier than the sell-side, but also highly complementary to traditional factors.
- **Estimote FES Model.** Diving into detailed Estimote estimates, we find that accuracy can be further improved along three dimensions: the freshness of the estimates, analyst experience (proxied by the number of previous estimates), and analyst skill (weighted by past performance or accuracy of each analyst). We then introduce a smart Estimote consensus called FES (Freshness, Experience, and Skill).
- **Smart Strategies around Earnings Announcement.** We explore three different type of trading strategies around earnings releases using the Estimote data. The pre-earnings announcement strategy buys (and sells/shorts) stocks based on earnings revisions in the week before the earnings reporting date. PEAD (Post Earnings Announcement Drift) strategy attempts to capture the drift alpha immediately after the earnings announcement, based on earnings surprise. Lastly, we propose a low risk long-only strategy by avoiding earnings risk and earnings uncertainty.
- **Enhanced Value Strategies.** Many fundamental and quantitative strategies explicitly or implicitly rely on earnings and revenue estimates. For long-term value investors, we show how Estimote data and our FES model can be used to boost performance. In the end, we also overlay our enhanced value strategy with a low risk tilt (by avoiding earnings uncertainty) to further improve return and reduce risk.



Source: gettyimages.com

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A LETTER TO OUR READERS

Introducing Crowdsourcing Big Data Earnings/Revenue Estimates

As argued in our previous research (see Luo, et al [2017a, 2017b, and 2017c], we believe that the future of active investing rests on the ability to incorporate alternative Big Data, using sophisticated machine learning techniques. In this paper, we demonstrate alternative data using Estimize.

Earnings and revenue estimates are arguably the most important drivers of stock returns and risks. Traditionally, investors collect estimates from the sell-side brokerage firms. Data vendors such as S&P Capital IQ (CIQ), Institutional Brokers' Estimate System (IBES), and Bloomberg Finance LLC provide both aggregated consensus and detailed estimates. Many fundamental (e.g., discounted cash flow models) and quantitative factors (e.g., earnings yield, earnings growth, earnings revision, ROE) explicitly or implicitly rely on predictions of future earnings and revenue. Gaining an edge with even slightly better earnings estimates can lead to tremendous alpha in the long run.

In this research, we study an alternative analyst estimate database called Estimize. The firm started the business by collecting buy-side earnings estimate data. In recent years, Estimize has significantly expanded the coverage. Now, not only finance professionals, but even students and professors may participate. The beauty of crowdsourcing is "the more the merrier".

We find that Estimize earnings estimates to be more accurate and timelier than traditional sell-side consensus, especially for large-cap household names and as we move closer to the actual earnings announcement date. Estimize data is highly complementary to traditional data sources, factors, and investment strategies.

Furthermore, as expected, not every analyst and estimate is created equally. The fresher the submission, the more accurate the prediction tends to be. We also find analyst experience (proxied by the number of past estimates provided by an analyst) and skill (measured by the estimation errors of each analyst) to be predictive of future performance. We introduce our Estimize FES (Freshness, Experience, and Skill) model by weighting each earnings estimate differently.

Lastly, we use a suite of examples to show how our Estimize FES model can be used in an event-driven context by trading both pre-earnings releases and to capture PEAD (post earnings announcement drift). For long-term value investors, we also demonstrate how our enhanced low risk value strategies can deliver superior alpha with low volatility.

Regards,

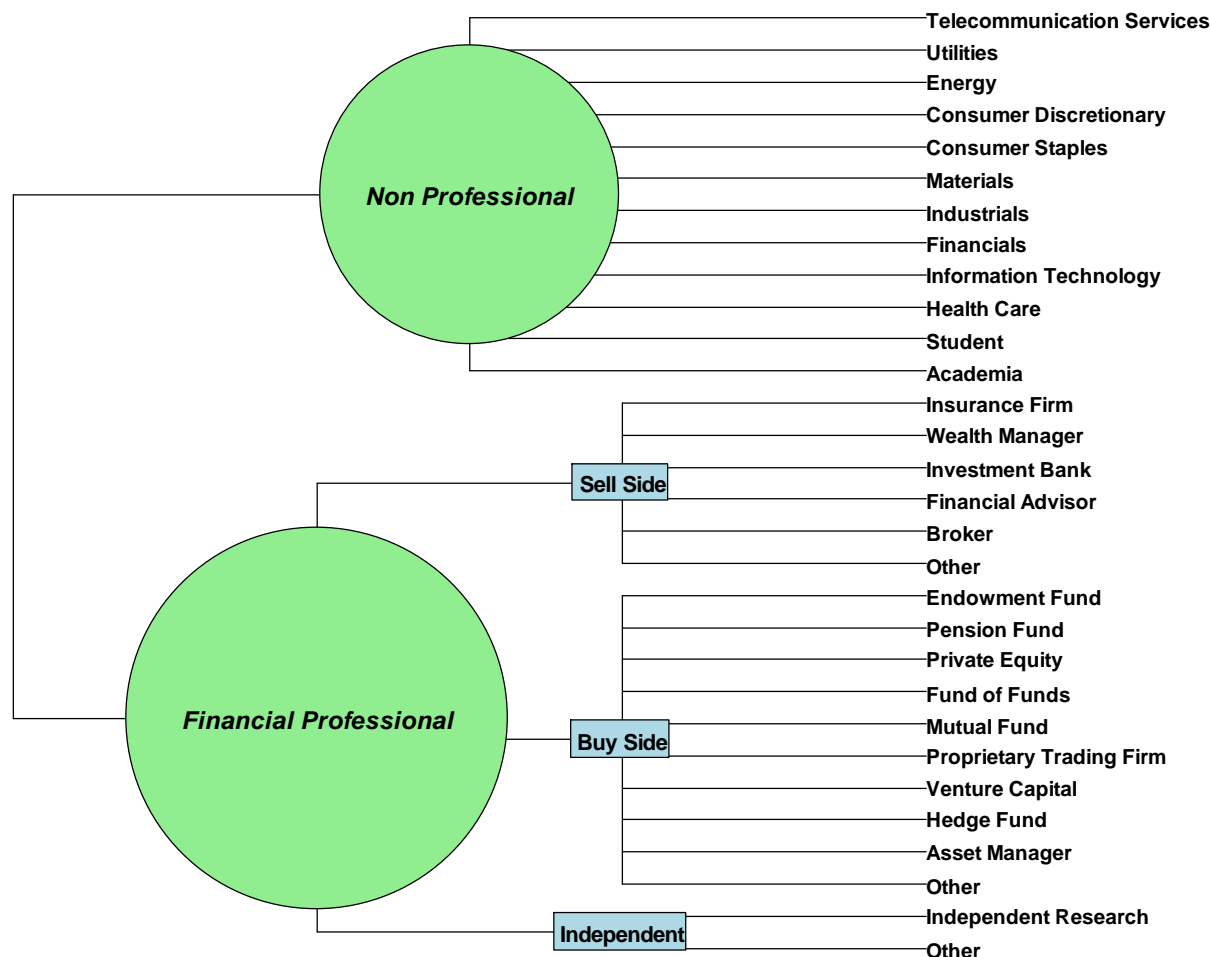
Yin, Javed, Sheng, Gaurav, Kartik, and Luo's QES team

THE BASICS OF ESTIMIZE

Both fundamental analysis (e.g., discounted cash flow analysis) and quantitative models (e.g., earnings yield, earnings revision) critically depend on an accurate estimate firms' future earnings and revenue. Traditionally, investors collect estimates from the sell-side brokerage firms. Data vendors such as S&P Capital IQ (CIQ), Institutional Brokers' Estimate System (IBES), and Bloomberg Finance LLC provide both aggregated consensus and detailed estimates at the daily, weekly or monthly frequency. They usually offer live updates as well as historical dataset.

In this research, we explore an interesting alternative data source called Estimize, which crowdsources earnings and revenue estimates from thousands of contributors including not only finance professionals, but also analysts from different industries and academia. Investment professionals consist of sell-side, independent, as well as buy-side analysts from hedge fund, mutual fund and other institutional investors. Figure 1 shows detailed classification of contributors.

Figure 1 Contributors to the Estimize database



Sources: Estimize, Wolfe Research Luo's QES

BREAKDOWN OF ESTIMIZE CONTRIBUTORS

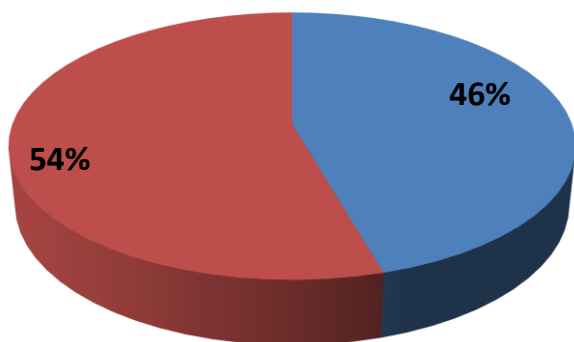
Interestingly, more than half the Estimate estimates are from non-financial professionals (see Figure 2). Among the finance professionals, sell-side accounts for only half of the estimates, while the other half splits quite evenly between buy-side and independent researchers.

There are questions such as why a buy-side analyst would ever want to participate, or what the motivation would be for a student to spend the time on building earnings forecast models. Among the many possible answers, the most appealing one is personal career development. In the end, there is probably nothing better than a great track record independently verified by the data vendor to present to potential employers.

Figure 2 A Breakdown of Estimate contributors

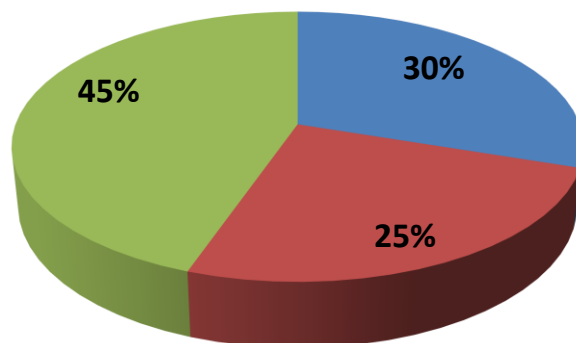
A) Breakdown of Estimate data

■ Finance Professionals ■ Non-professionals



B) Breakdown of financial professional

■ Independent ■ Buy Side ■ Sell Side



Sources: Estimate, Wolfe Research Luo's QES

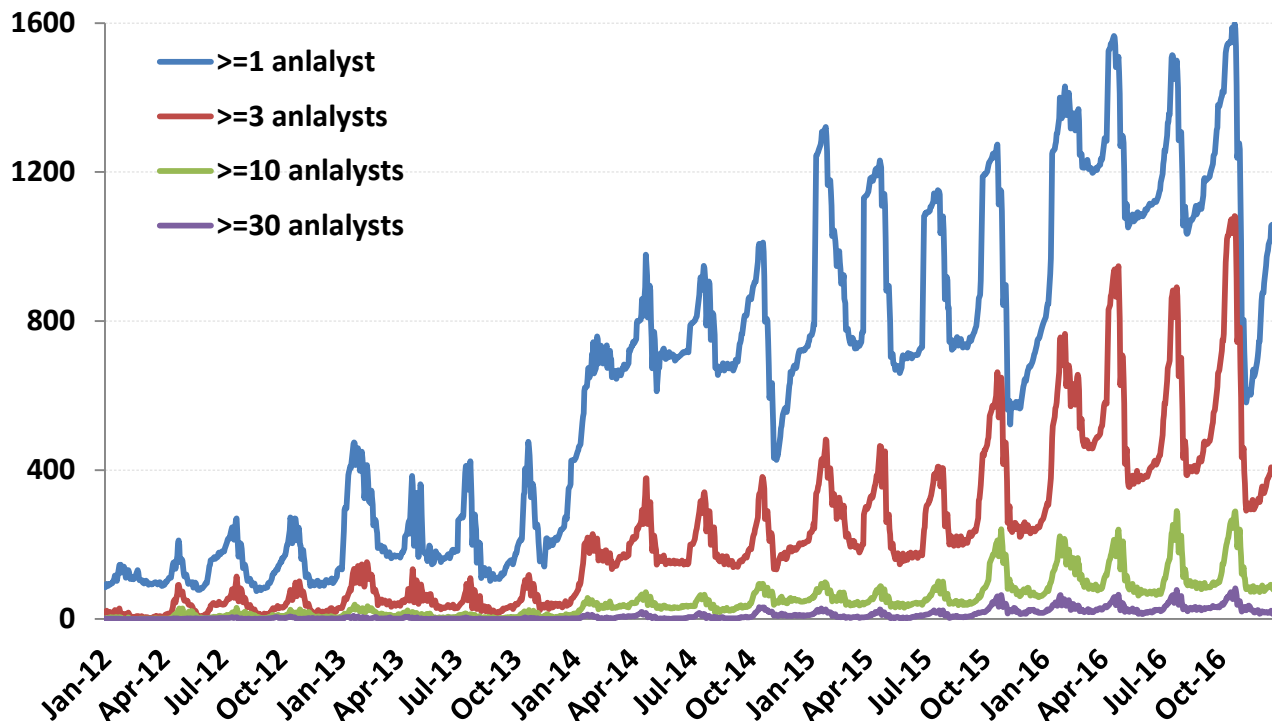
ESTIMIZE DATA COVERAGE

As a relatively new vendor, Estimate has a much shorter data history than the conventional data providers like IBES or CIQ. Prior to 2012, there were only a few sparse data points from Estimate; therefore our analysis starts from 2012.

Figure 3 shows the daily number of companies covered by the Estimate database that are also in the Russell 3000 universe. Coverage is defined as the number of unique companies which has certain number of estimates on a given date before a company announces its earnings. Unlike most sell-side analysts, most other contributors only submit their estimates prior to a company's next earnings release date. Therefore, right after a company reports its current quarterly earnings (and before next quarter announcement date comes close), there is typically a steep decline in coverage. That is why we see a strong (quarterly) seasonal effect, due to the fact that most estimates are contributed right before the actual announcement date.

The coverage in the Estimize database has been improving over time, especially after 2014. Currently, there are close to 1,600 companies in the Russell 3000 universe with at least one analyst coverage.

Figure 3 # of companies (in the Russell 3000 index) with Estimize analyst coverage



Sources: Estimize, FTSE Russell, Wolfe Research Luo's QES

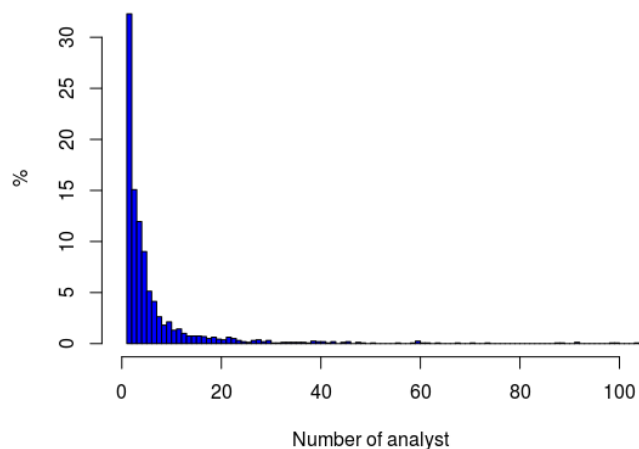
ESTIMIZE DATA DISTRIBUTION

The data in the Estimize database is highly skewed. As shown in Figure 4 (A), over 30% of companies have only one analyst contributing and only around 200 firms with coverage of more than 10 analysts. On the other side, the distribution also has a fat right tail, i.e., there are a few large household companies with over 100 analysts in the dataset. The maximum number of analysts contributing to a single stock EPS in Estimize is over 200, while in the IBES and CIQ databases, the maximum number of analysts is around 50.

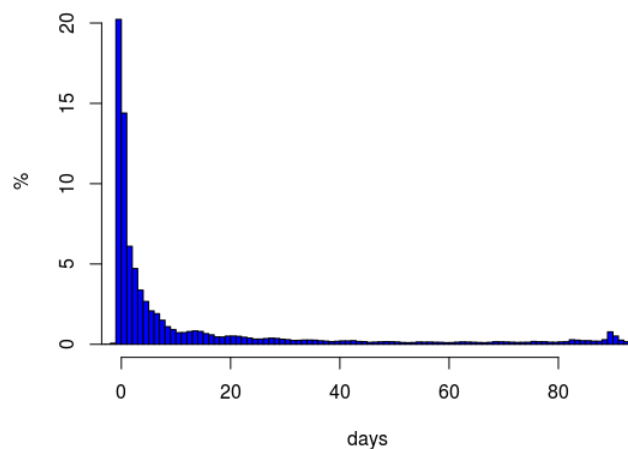
We can also see that most earnings estimates are submitted a few days before the actual announcement date (see Figure 4 B). The distribution again highly skewed to the left, where a few analysts provide long-term estimates quarters ahead.

Figure 4 A The distribution of Estimize estimates

A) Number of analysts



B) Number of days before earnings report

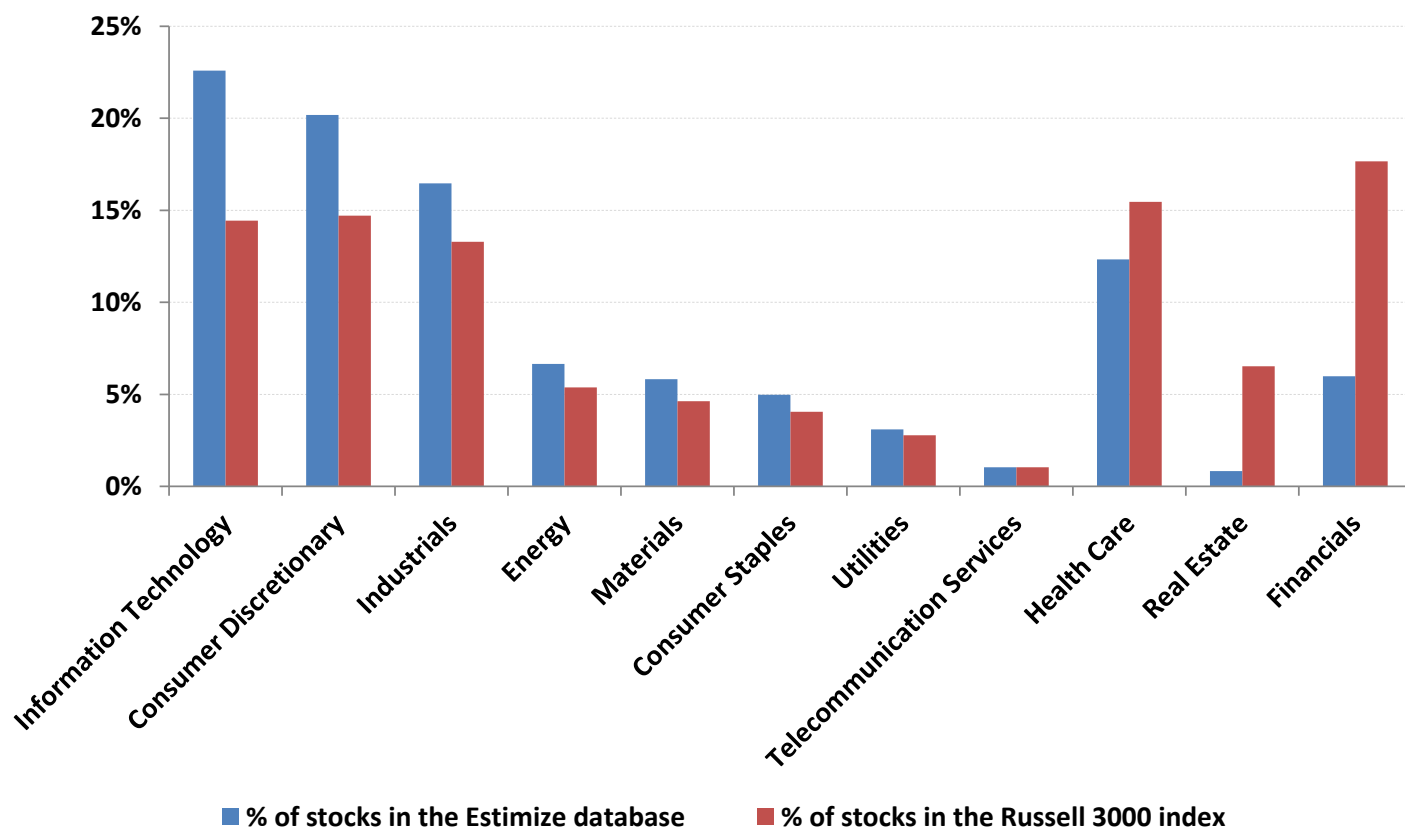


Sources: Estimize, Wolfe Research Luo's QES

ESTIMIZE COVERAGE BY SECTOR

The Estimize data also has heavy sector biases. Compared to the benchmark, there are more estimates for information technology, consumer discretionary and industrials, while much fewer data points for financials, real estate, health care and utilities (see Figure 5). Certainly, the “popular” sectors such as information technology and consumer discretionary receive far more interest, especially from non-professionals. On the other hand, the specialized industries like financials and health care have fewer analysts with the necessary skills.

Figure 5 Estimote data sector distribution



Sources: Estimote, S&P Capital IQ, FTSE Russell, Wolfe Research Luo's QES

THE ACCURACY OF CROWDSOURCING

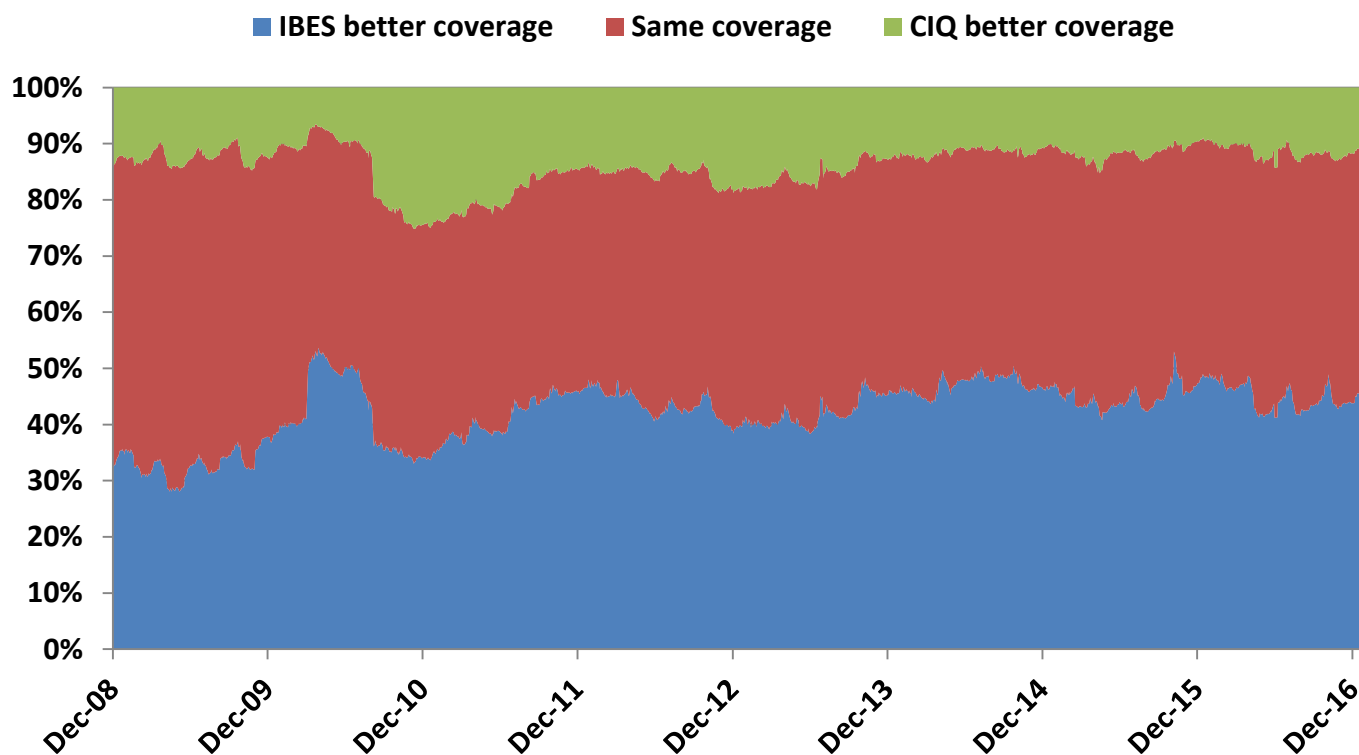
The first question that we try to address is whether Estimize estimates are more accurate than traditional sell-side consensus. The answer is not necessarily straightforward and you might be surprised.

TRADITIONAL SELL SIDE ESTIMATES: CIQ VERSUS IBES

Before we dive into the Estimize data, let's take a closer look at the two major conventional sell-side consensus data providers: IBES and CIQ.

For Russell 3000 companies, IBES consensus has a much longer history than CIQ. On average, IBES also has slightly more analysts covering a given stock than CIQ, but the difference is insignificant, as almost half companies have exactly same number of analysts in the two databases (see Figure 6).

Figure 6 Quarterly earnings estimate comparison, IBES versus CIQ

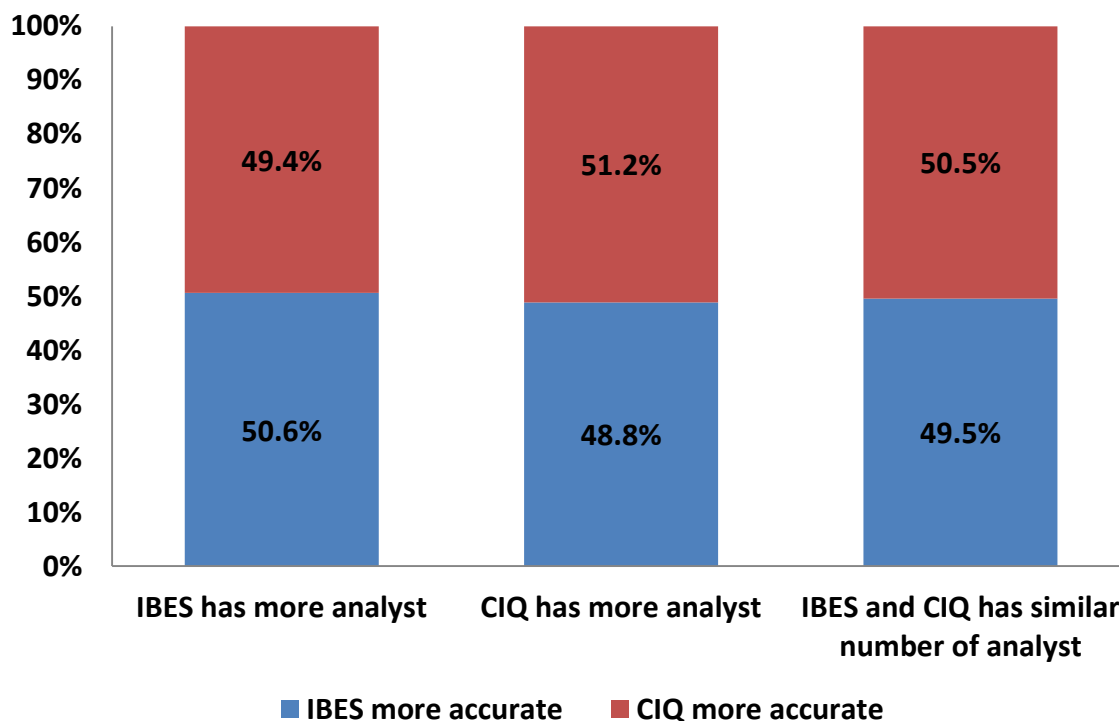


Sources: IBES, S&P Capital IQ, FTSE Russell, Wolfe Research Luo's QES

Between IBES and CIQ, the accuracy critically depends on coverage. As shown in Figure 7, the vendor that has more analysts covering is always more accurate than the other, while for those companies with same number of analysts, the two databases have similar accuracy. This again reflects the philosophy that consensus predictions tend to be more accurate than any individual analysts.

In general, IBES and CIQ have very similar accuracy. This is as expected, because most bulge bracket banks participate in all major consensus surveys; therefore, there is a significant overlap between the two databases.

Figure 7 IBES versus CIQ accuracy



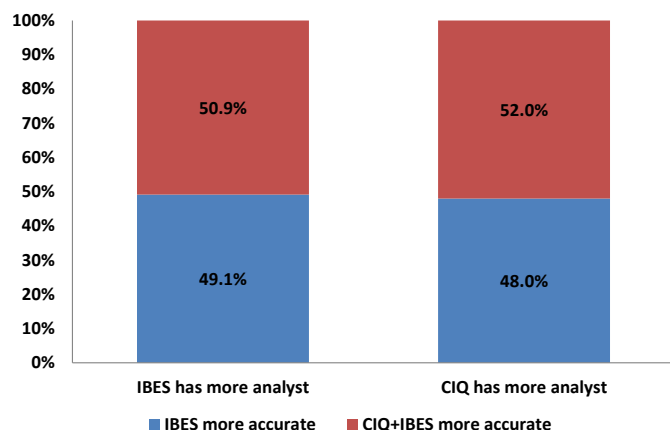
Sources: IBES, S&P Capital IQ, FTSE Russell, Wolfe Research Luo's QES

What is more interesting is that when we combine the earnings estimates from IBES and CIQ, the blended forecast beats both underlying data sources, regardless which vendor has a larger number of analysts (see Figure 8).

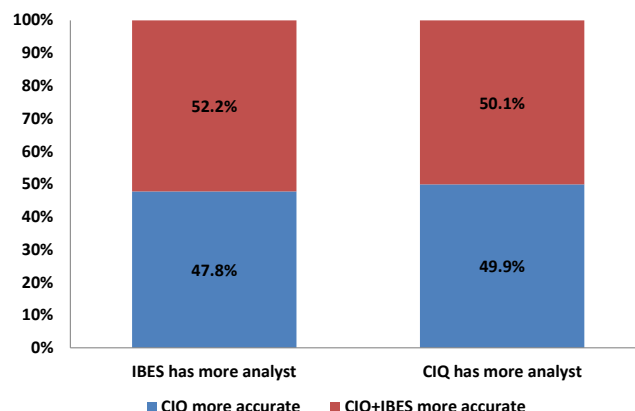
For the rest of this paper, we shall use this combined CIQ+IBES EPS estimate as our benchmark or a proxy for sell-side consensus.

Figure 8 Combining IBES and CIQ

A) Combining CIQ and IBES more accurate than IBES



B) Combining CIQ and IBES more accurate than CIQ



Sources: IBES, S&P Capital IQ, FTSE Russell, Wolfe Research Luo's QES

ESTIMIZE CROWDSOURCING VERSUS THE SELL-SIDE

Given that the two traditional sell-side consensus databases have the same accuracy, now we shift our attention to Estimize. We want to assess whether crowdsourced earnings and revenue estimates from Estimize are more accurate than sell-side consensus.

Overall accuracy for EPS and Revenue estimates

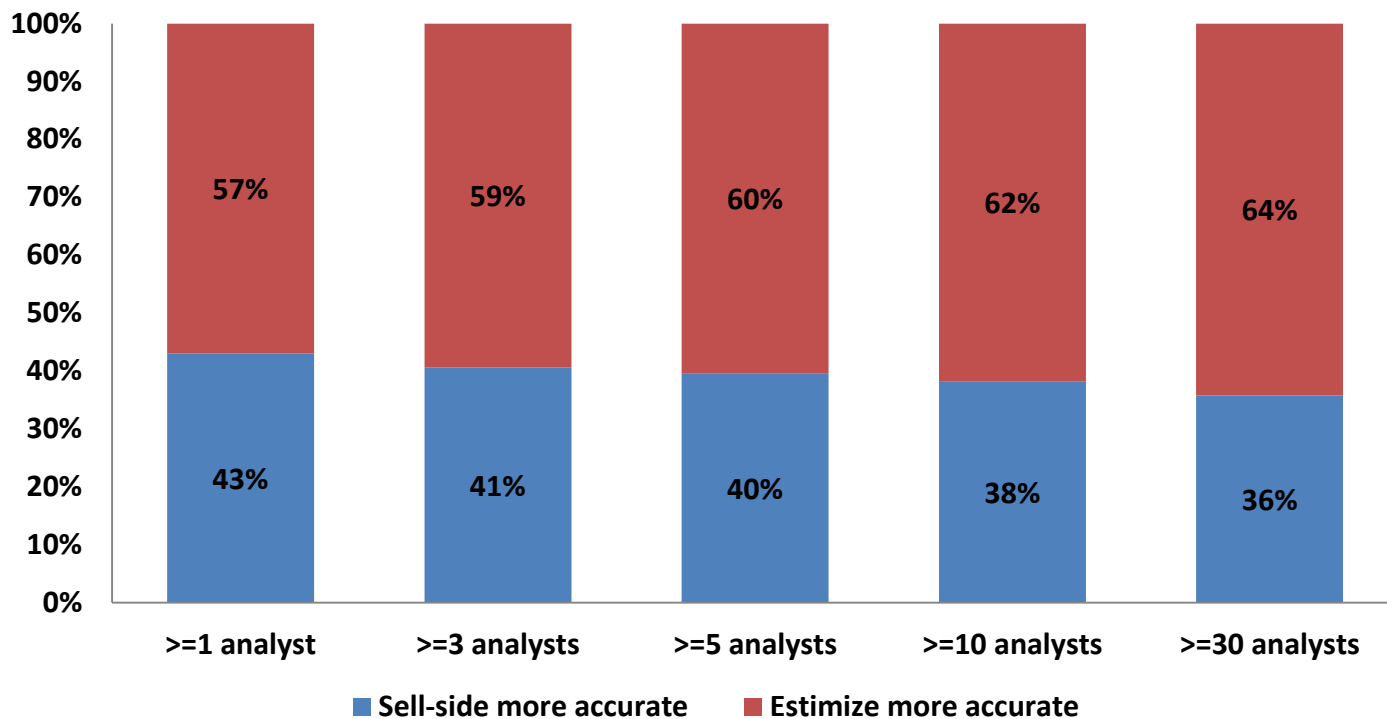
It is interesting to note that Estimize earnings estimates are significantly more accurate than the sell-side even for those companies with few analysts (see Figure 9 A). As the number of analysts from the Estimize database increases, the accuracy also improves. For those household names over 30 analysts, Estimize is almost twice more accurate than the sell-side.

On the revenue side, the difference in accuracy is much more muted (see in Figure 9 B). However, we do observe that as number of analysts goes up, the accuracy of Estimize revenue estimates also grows.

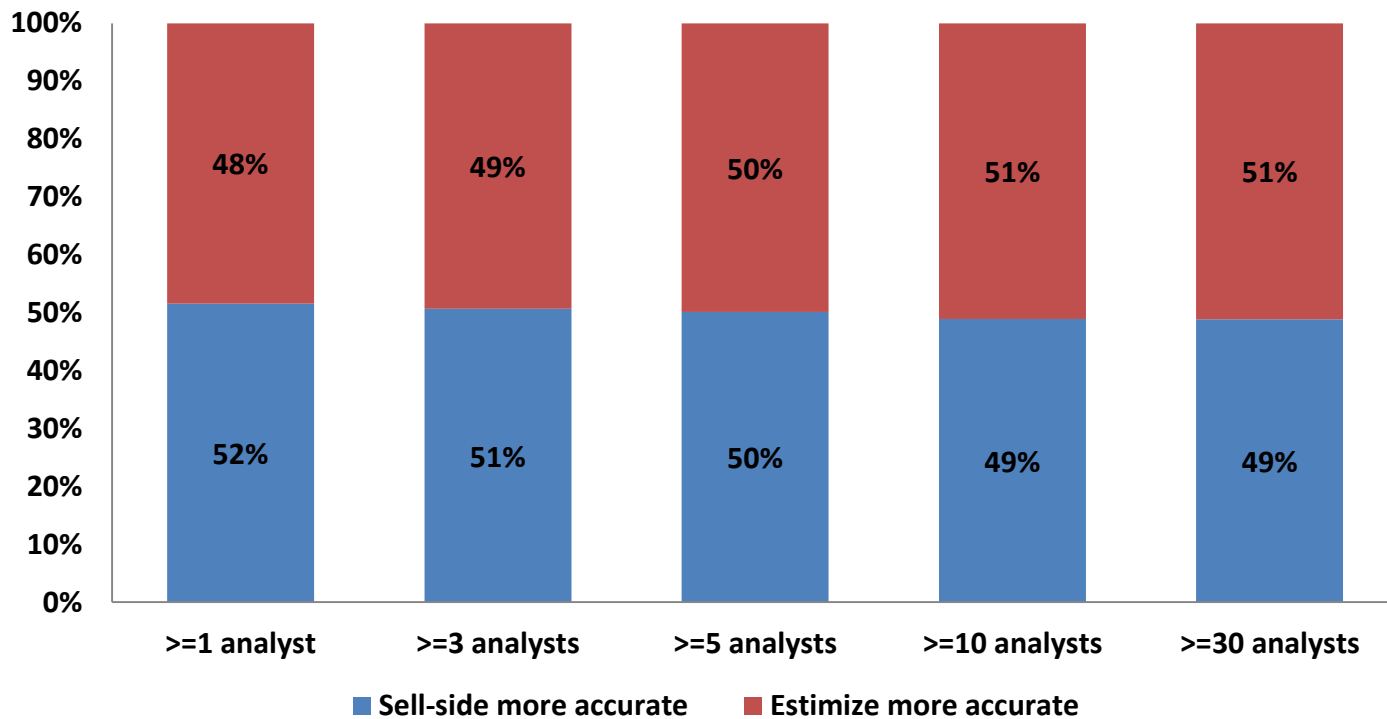
In the rest of the paper, we will focus on the EPS estimates from Estimize, since earnings estimates are considerably more accurate than the traditional sell side.

Figure 9 Accuracy, Estimote versus the sell-side consensus

A) EPS estimate accuracy



B) Revenue estimate accuracy

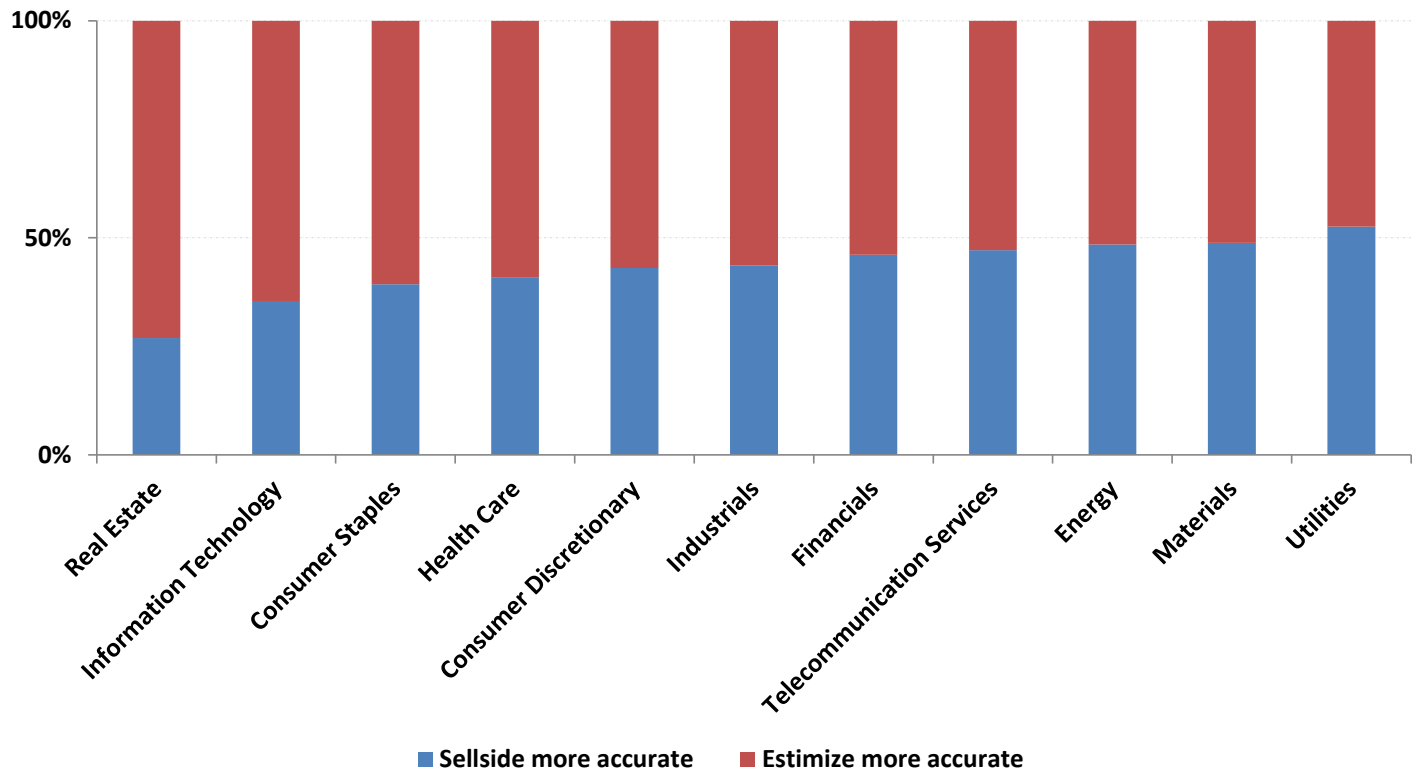


Sources: Estimote, IBES, S&P Capital IQ, FTSE Russell, Wolfe Research Luo's QES

Accuracy by Sector

As shown in Figure 10, Estimote's EPS accuracy varies substantially across sectors. Crowdsourced earnings appear to be far more accuracy in the real estate and information technology sectors, but struggle in the more specialized industries such as the material and utilities.

Figure 10 Estimote EPS accuracy by sector



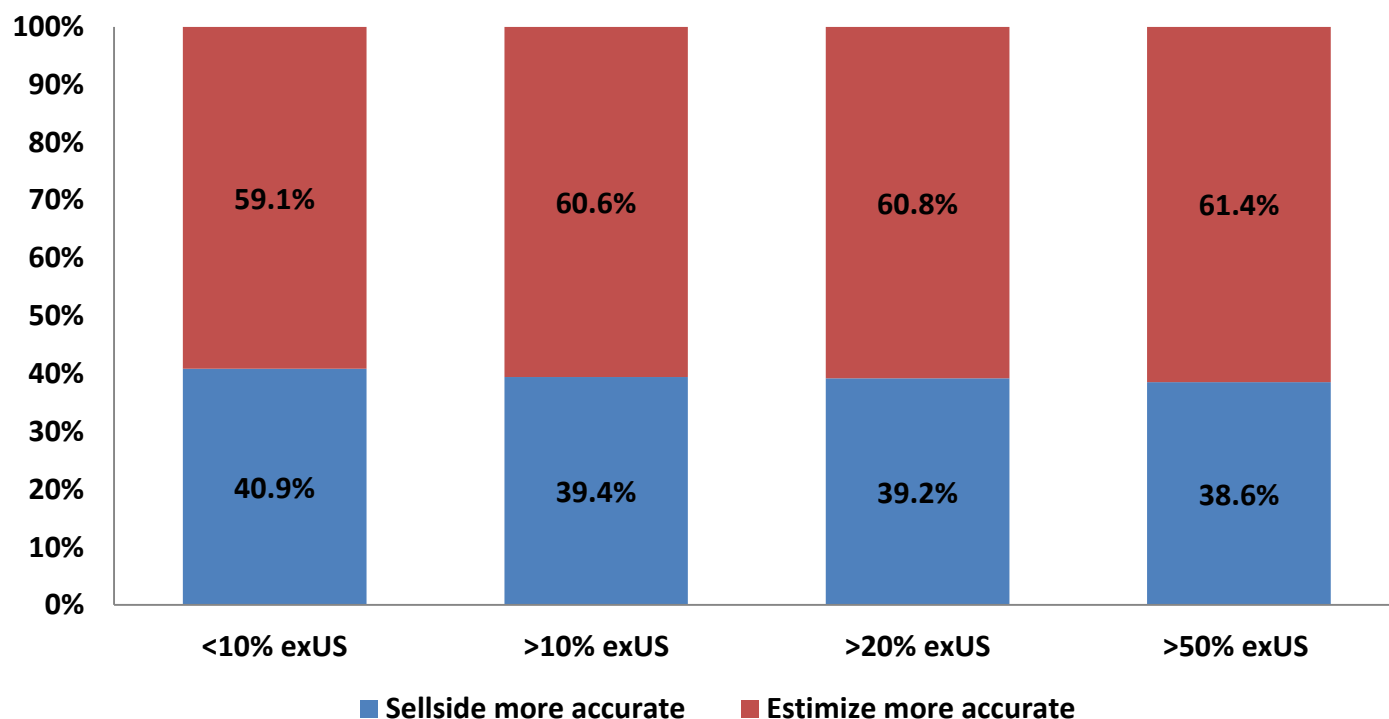
Sources: Estimote, IBES, S&P Capital IQ, FTSE Russell, Wolfe Research Luo's QES

Domestic versus multinational firms

Next, we want to understand whether Estimote is better at predicting earnings for multinational companies with significant global exposure than domestic firms? As shown in Figure 11, the larger the international exposure that a company has, the more accurate the Estimate data tends to be. It is possible that Estimote contributors can be based anywhere in the world, while sell-side brokers are mostly domestic. Moreover, multinational firms are generally larger and attracting more attention from the crowd. As shown in the previous section, the more "popular" a company is, the more analysts participate in the earnings estimate and therefore, the more accurate the prediction tends to be.

Please note that we source international exposure data from Compustat's business segment database.

Figure 11 Estimize accuracy, domestic versus multinational firms



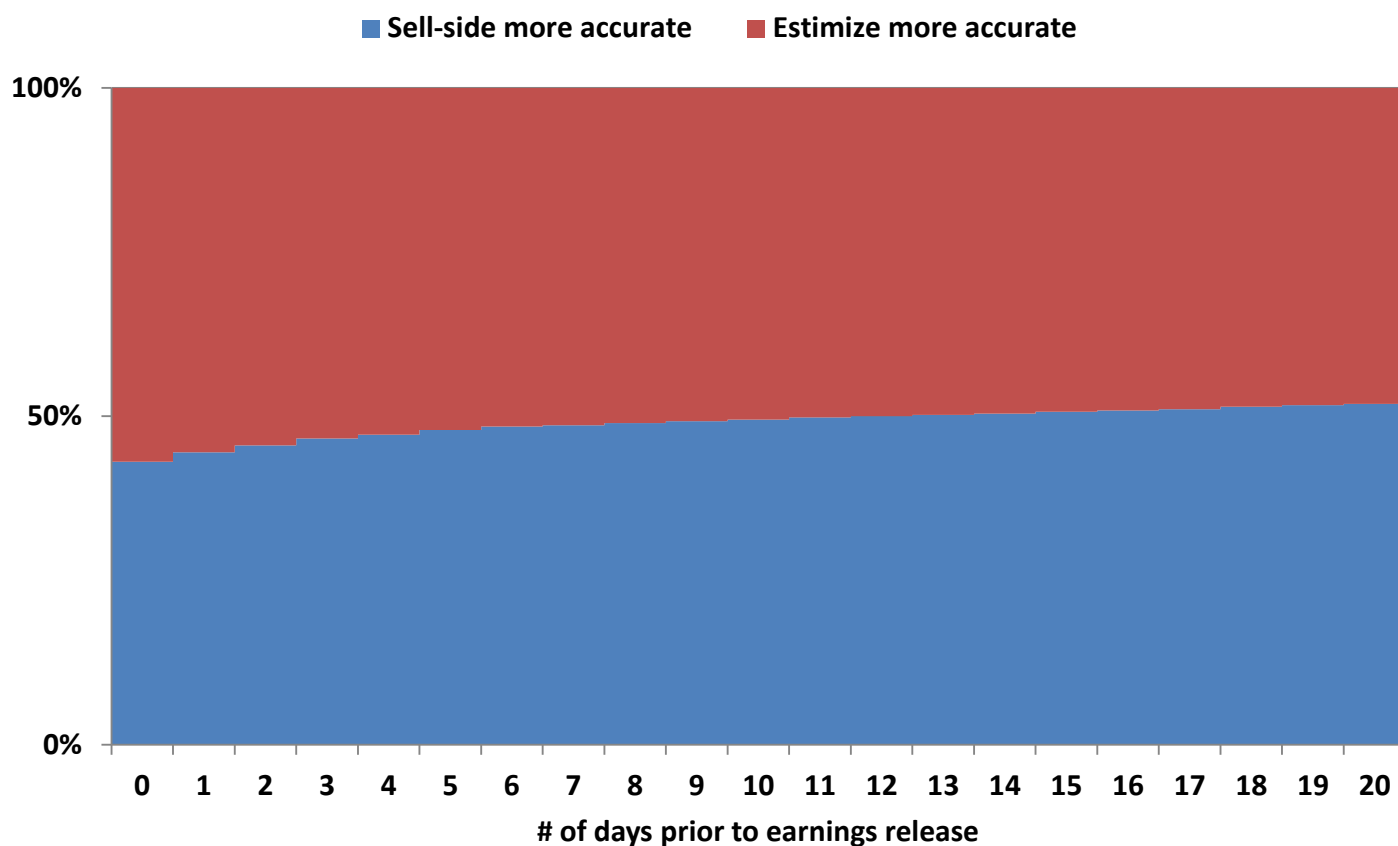
Sources: Estim�, IBES, S&P Capital IQ, FTSE Russell, Wolfe Research Luo's QES

TIMELINESS OF THE ESTIMIZE DATA

As a result of the heightened regulation around sell-side research (e.g., Reg FD in 2000, global research settlement in 2002, and the recent MiFID II), it takes considerable efforts for a sell-side analyst to update her earnings estimates. Therefore, it is unlikely for an analyst to modify her predictions frequently, especially right before a covered company releases earnings. On the other hand, the compliance burden is likely to be much lighter for a crowdsourcing database such as Estim�. We would expect Estim� estimates to be timelier.

Figure 12 shows the accuracy of the Estim� EPS estimate as a function of the number of days prior to an earnings announcement. As earnings release date approaches, the Estimate data becomes more and more accurate. This suggests that Estim� provides timelier estimates, while sell-side analysts are better at predicting earnings over a longer horizon.

Figure 12 Estimote EPS accuracy as a function of the number of days prior to earnings announcement



Sources: Estimote, IBES, S&P Capital IQ, FTSE Russell, Wolfe Research Luo's QES

DIGGING DEEPER INTO ESTIMIZE DETAILS

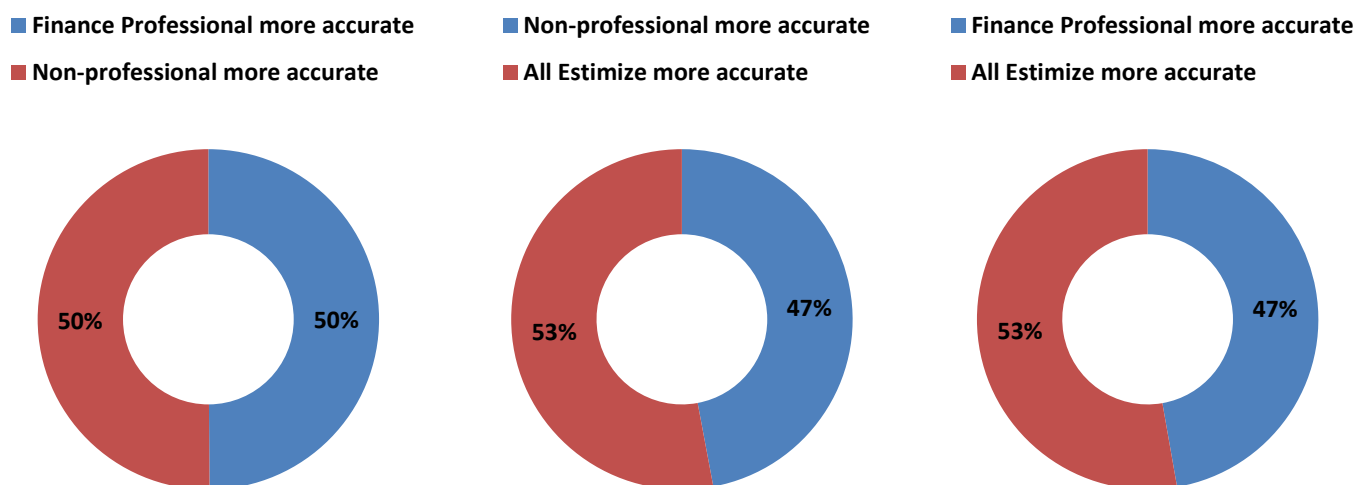
From Estimate detailed analyst-level database, we are able to extract useful information from the metadata of individual analysts as well as certain characteristics of their estimates. In this section, we take a close look at Estimate details. We search for common features leading to more accurate estimates, and smartly weight top performing analysts to achieve a higher accuracy.

FINANCE PROFESSIONALS VERSUS NON-PROFESSIONALS

We first compare the EPS prediction accuracy of finance professionals with non-professionals. It is ironic to note that finance professionals are not necessarily more accurate than non-professionals (see Figure 13). There are a few possible explanations. First of all, professional investors from either the buy-side or the sell-side tend to cover far more stocks than non-professionals. There is also a sample selection bias argument – professionals are assigned to a given sector, regardless if the sector is easy or difficult to analyze. On the other hand, non-professionals choose those industries and companies that they feel most comfortable to analyze.

Due to the diversification benefit, i.e., professionals and non-professionals do not always arrive at the same conclusions, combined forecasts are more accurate than either professionals or non-professionals.

Figure 13 Financial professional versus non-professionals

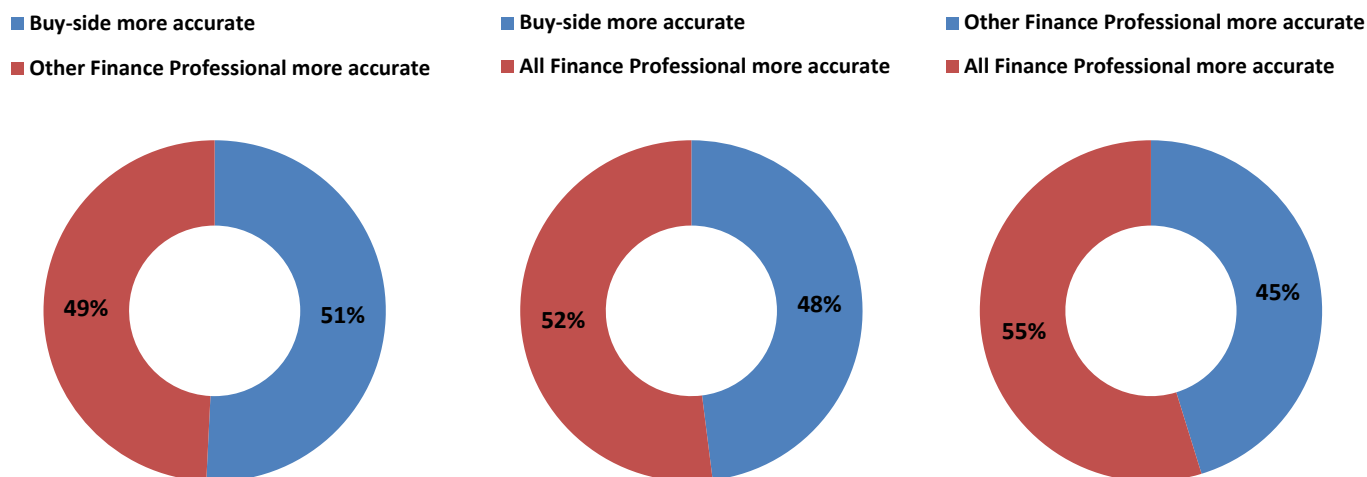


Sources: Estimate, IBES, S&P Capital IQ, FTSE Russell, Wolfe Research Luo's QES

BUY-SIDE VERSUS OTHER FINANCE PROFESSIONAL

We next investigate, among the professionals, whether buy-side contributors have more accurate estimates than other professionals. Figure 14 shows that, on average, buy-side analysts are slightly more accurate than other finance professionals. However, similar to what we have seen in the previous section, combining the buy-side and other professionals further boosts the prediction accuracy, due to the diversification benefit.

Figure 14 Buy-side analysts versus other finance professionals



Sources: Estimote, IBES, S&P Capital IQ, FTSE Russell, Wolfe Research Luo's QES

FRESHNESS OF THE ESTIMATES

Recall that Estimote data is more accurate than the sell-side consensus, as we approach closer to the earnings announcement date (see Figure 12). The timeliness is one of the major benefits from Estimote, because contributors can update their numbers easily without the fierce compliance burden faced by sell-side analysts.

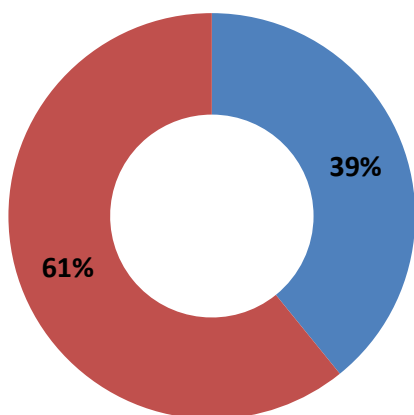
Therefore, intuitively, fresher estimates from contributors should have better accuracy. To test this hypothesis, for each stock at each announcement date, we calculate two average estimates, one based on “older” estimates and the other based on “newer” estimates. We define “older” estimates as those created before median time among all the estimates for the given stock at a given release date. Similarly, “newer” estimates are created post the median time for each stock at each release date. Figure 15 (A) shows that “newer” estimates are far more accurate than “older” estimates.

Instead of splitting the universe of all estimates by the median, we can further refine our timeliness into decile portfolios. We define the “newest” estimates as the top decile the freshest estimates for each stock at each release and the “oldest” estimates as the bottom decile the stalest estimates. The difference grows even larger, as we move from the median split into the decile portfolios (see Figure 15 B).

Figure 15 Freshness of the estimates

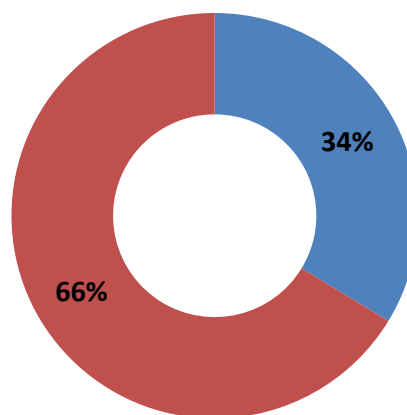
A) Comparing the above and below median freshness

- Older estimates, more accurate
- Newer estimates, more accurate



B) Comparing top and bottom decile freshness

- Oldest estimate, more accurate
- Newest estimates, more accurate



Sources: Estimote, IBES, S&P Capital IQ, FTSE Russell, Wolfe Research Luo's QES

ANALYST EXPERIENCE

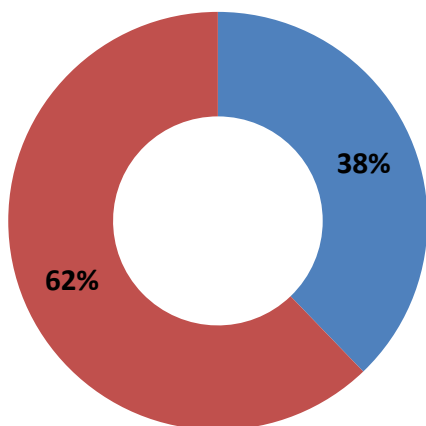
Next, we explore whether the experience of the contributors lead to higher accuracy. We measure the experience of an analyst by the number of her previous contributed estimates. This not only reflects the productivity of an analysts, but also the length that she has been participating in the database.

Similar to the previous section, we create two average estimates for each stock at each release date, based on the number of previous estimates an analyst contributed at the time. We consider those analysts who have more contributions in the past as more experienced. Figure 16 (A) and (B) show that more seasoned analysts certainly beat those less experienced.

Figure 16 Experience of the analyst

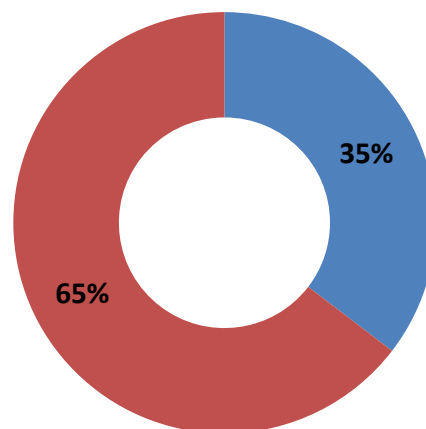
A) Comparing above and below median experience

- Below median experience analysts, more accurate
- Above median experience analysts, more accurate



B) Comparing top and bottom decile experience

- Bottom decile experience analysts, more accurate
- Top decile experience analysts, more accurate



Sources: Estimize, IBES, S&P Capital IQ, FTSE Russell, Wolfe Research Luo's QES

ANALYST SKILL

Another important aspect of an analyst is her skill. If we assume that an analyst's skill is persistent over time, then more skillful analysts should provide more accurate estimates in the future.

The question now is how to measure analyst skill. An obvious choice is the past track record, or historical accuracy of the analyst. We also need to account for analyst coverage changes, as she may switch her interest over time. We define estimation error as:

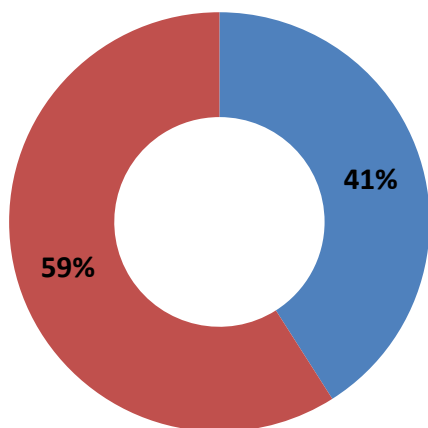
$$EstimationError = \frac{|ActualEPS - EstimatedEPS|}{StockPrice}$$

We constructed two average estimates for each stock at each release date – one based on more skillful analysts (whose previously estimates have below the median estimation error) and another based on less skillful analysts (whose previous estimates have above the median error). The result is also as we expected, the skillful analysts is more accurate than the less skillful analyst as shown in Figure 17 (a). The spread between the skillful analyst and less skillful analyst is larger at extreme level Figure 17 (b).

Figure 17 Analyst skill

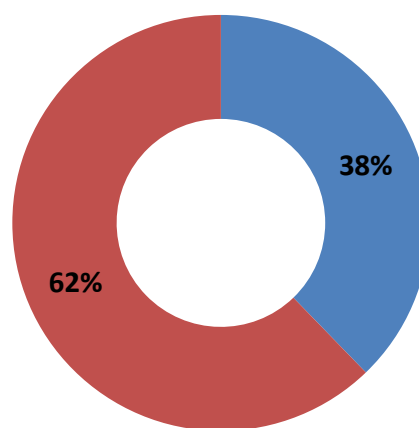
A) Comparing above and below median skill

- Below median skill analysts, more accurate
- Above median skill analysts, more accurate



B) Comparing top and bottom decile skill

- Bottom decile skill analysts, more accurate
- Top decile skill analysts, more accurate



Sources: Estimote, IBES, S&P Capital IQ, FTSE Russell, Wolfe Research Luo's QES

PUT EVERYTHING TOGETHER – THE FES MODEL

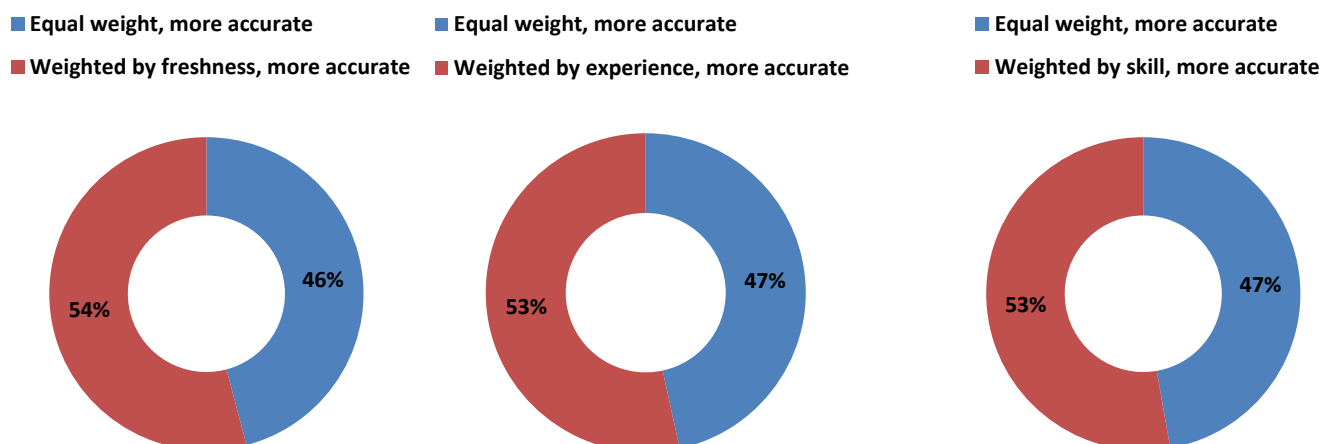
Based on the previous three sections, three important aspects of the detailed estimates determine the accuracy of EPS prediction: freshness of the estimates, analyst experience, and analyst skill.

Naturally, instead of equal weighting all estimates, we can weigh the Estimote estimates by each of the three aspects – the Freshness, Experience, and Skill, i.e., the FES model:

- Weighted by the freshness of the estimates: the fresher the estimates, the higher the weight. In our implementation, we decay the weight exponentially, with a half-life of one week.
- Weighted by analyst experience (i.e., the number of previous estimates): the more experience an analysts has, the higher the weight. We construct the weight point-in-time to avoid any look-ahead bias. For a given stock at a given date, we only count the total number of EPS estimates an analyst has contributed as of the time.
- Weighted by analyst skill (i.e., the previous estimate error rate): the more skillful an analyst, the higher the weight. Similarly, analyst skill is computed using a point-in-time database to avoid look-ahead bias.

Figure 18 shows that weighting EPS estimates by each of the three aspect delivers more accurate predictions than the headline Estimote EPS. For robustness, we only examine those stocks with at least three analysts coverage.

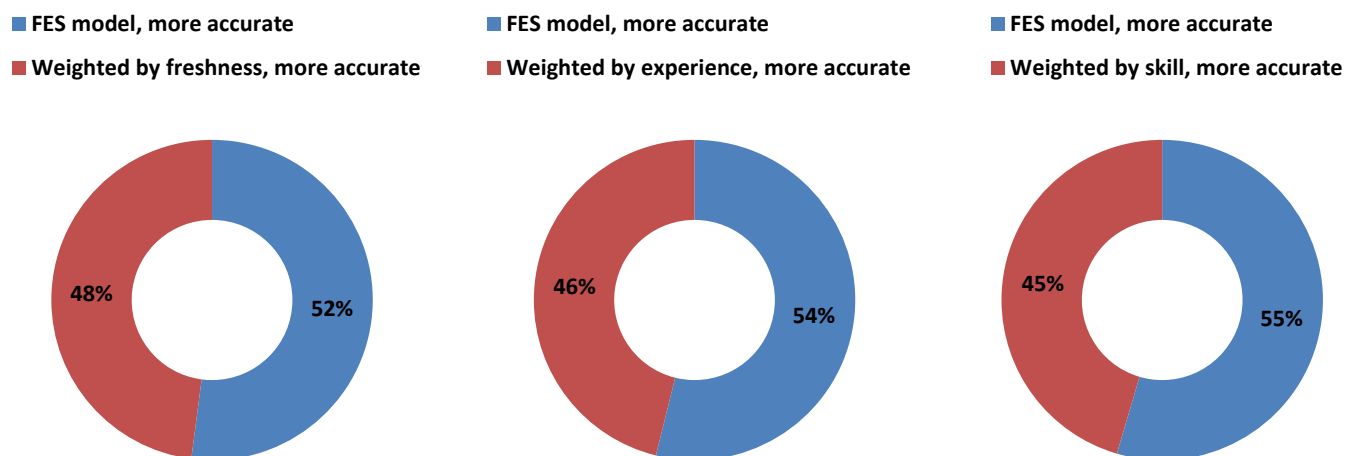
Figure 18 Weighting the estimates by the freshness, analyst experience, and analyst skill



Sources: Estimote, IBES, S&P Capital IQ, FTSE Russell, Wolfe Research Luo's QES

Combining all three dimensions – the freshness of the estimate, analyst experience, and analyst skill delivers the most accurate forecast. As shown in Figure 19, the FES model easily beats any single weighting schemes.

Figure 19 Estimote FES model versus single weighting scheme



Sources: Estimote, IBES, S&P Capital IQ, FTSE Russell, Wolfe Research Luo's QES

TRADING AROUND EARNINGS ANNOUNCEMENTS

The earnings announcement is among the most significant market moving corporate events. Since the crowdsourced Estimote EPS tend to be more accurate and complement traditional sell-side consensus, we can potentially make better investment decisions around earnings announcements.

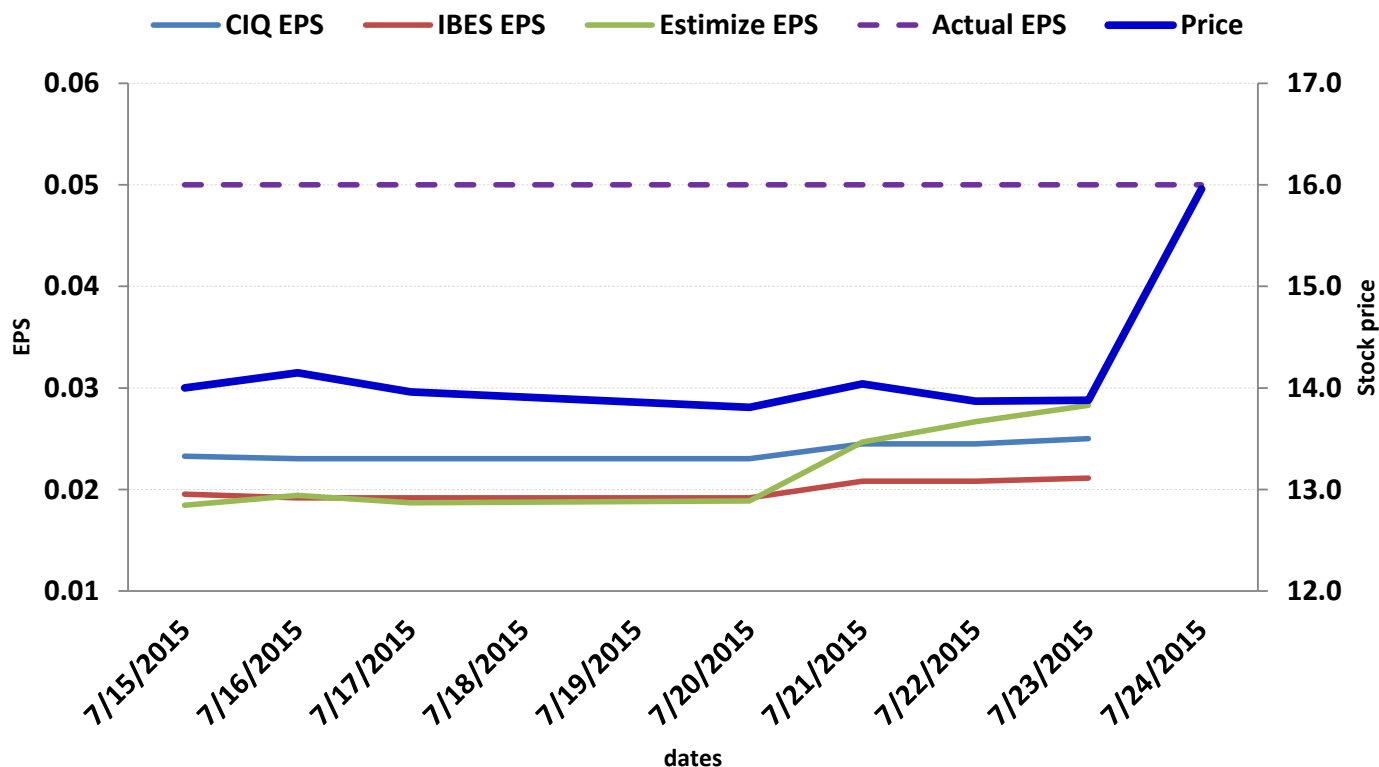
PRE-EARNINGS ANNOUNCEMENT STRATEGY

As a benchmark, we combine the quarterly EPS estimates from IBES and CIQ as the sell-side consensus. This data is updated at a daily frequency. At the same time, we also construct a daily Estimote aggregated EPS estimate, based on all the data submitted before market close. We use the FES model described in the previous section to represent Estimote estimates.

An example

Figure 20 shows an example of Pandora Media. The firm beat earnings expectations in the second quarter of 2015. Both IBES and CIQ EPS estimate rose slightly in the week before the earnings announcement. However, we can also see that Estimote registered an even larger increase. When the actual earnings hit the news as more than double the sell-side consensus, the stock price rallied 15% on the announcement date. This example gives us a hint that, if the consensus moves up right before earnings announcement, a company is more likely to beat the consensus.

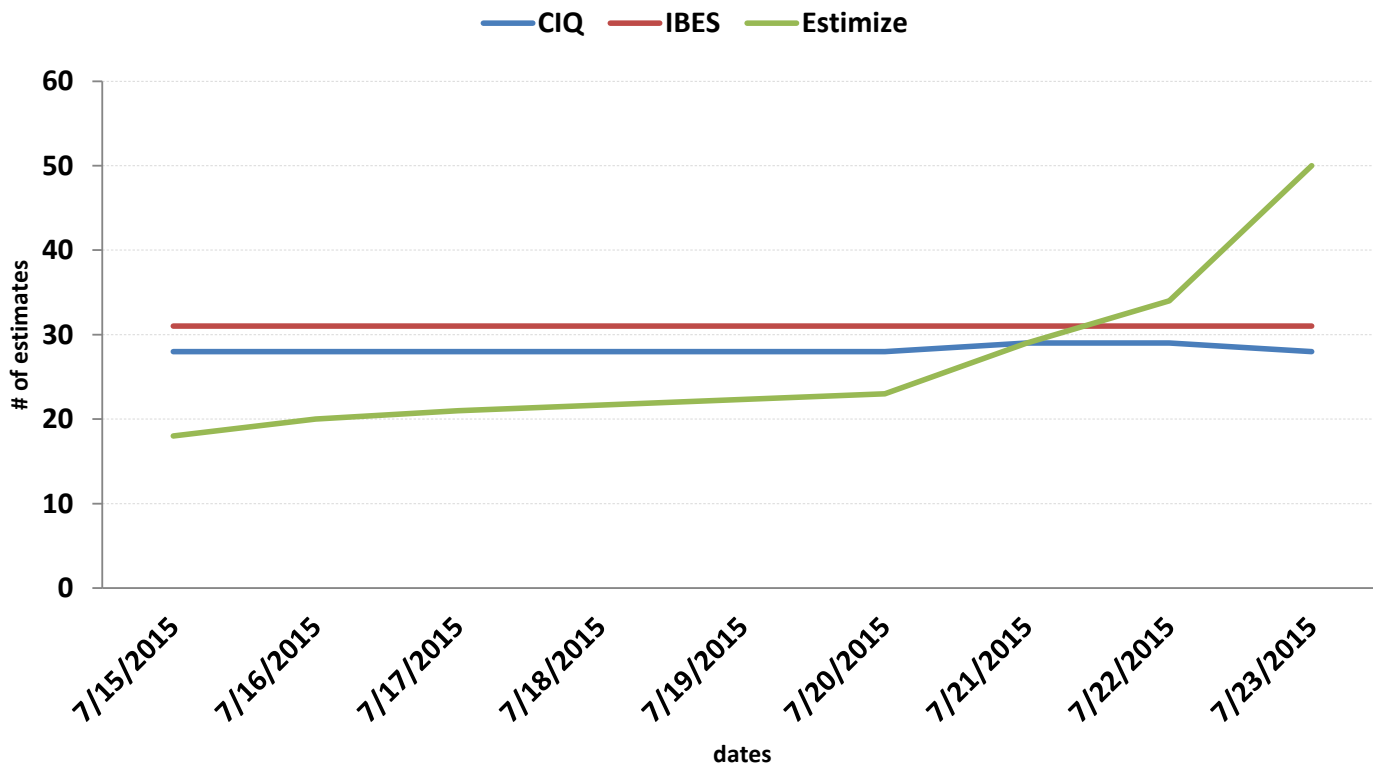
Figure 20 An example of Pandora Media before earnings announcement



Sources: Estimote, IBES, S&P Capital IQ, FTSE Russell, Thomson Reuters, Wolfe Research Luo's QES

When we look at the number of estimates used to compute the consensus EPS (see Figure 21), it is evident that, while the number of sell-side analysts are relatively constant, the number of estimates in the Estimate database jumped sharply immediately prior to the announcement date. We can see that the sell-side has a relatively stable number of analysts contributing, while Estimate has a significant number of people contributing in the last two days before the earnings announcement. In particular, in the last two days, the number of contributions in the Estimate exceeded both CIQ and IBES, and as a result, the Estimate estimate also became more accurate than the sell-side consensus.

Figure 21 Number of estimates available for Pandora Media before earnings announcement



Sources: Estimize, IBES, S&P Capital IQ, FTSE Russell, Thomson Reuters, Wolfe Research Luo's QES

Earnings revisions prior to announcement date leads announcement day return

We expect those analysts who revise their EPS estimates right before earnings announcement date to have higher conviction. Therefore, an upward EPS revision potentially leads to a more positive announcement day return. We define earnings revision $EarningsRevision_{i,t}$ for stock i at time t as:

$$EarningsRevision_{i,t} = \frac{EPS_{i,t} - EPS_{i,t-1}}{|EPS_{i,t-1}|}$$

Where,

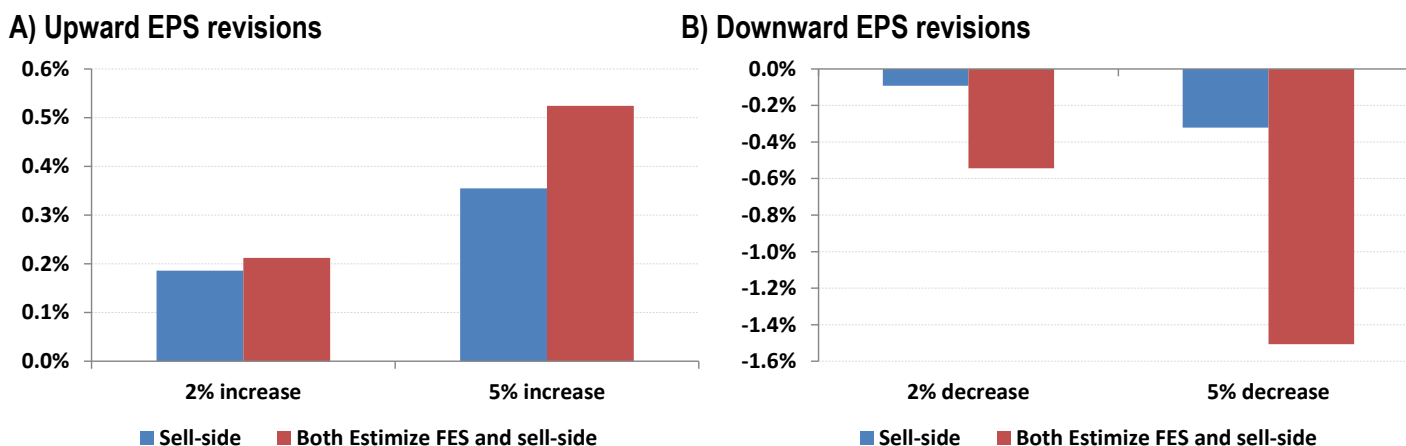
$EPS_{i,t}$ is the earnings per share for stock i at time t ,

$EPS_{i,t-1}$ is the earnings per share for stock i at one week ago

Figure 22 confirms our hypothesis:

- Upward (downward) EPS revisions in the week prior to earnings announcement lead to positive (negative) announcement day returns.
- Larger revisions in the week right before earnings announcement lead to larger announcement day return, for both upward and downward changes.
- When both Estimote FES and sell-side consensus revise EPS in the week prior to earnings announcement, in the same direction and magnitude, the announcement day excess return becomes even more significant.

Figure 22 Average excess earning announcement 1-day return



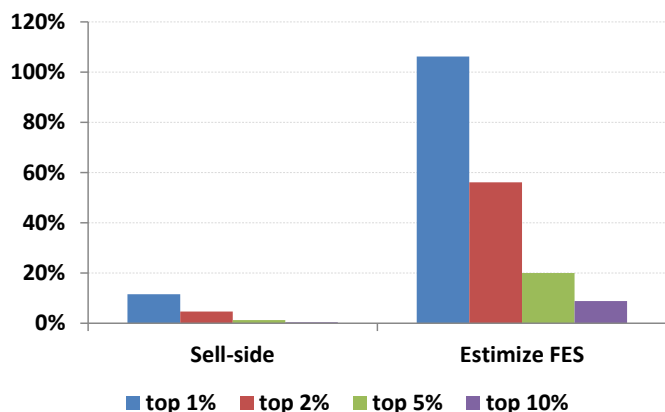
Sources: Estimote, IBES, S&P Capital IQ, FTSE Russell, Thomson Reuters, Wolfe Research Luo's QES

As discussed in the previous sections, because it is much easier for contributors to revise their estimates in the Estimote database than the sell-side, the most positive and negative Estimote earnings revisions tend to be far larger (see Figure 23). It is inappropriate to apply the same threshold of percentage EPS revisions for Estimote and the sell-side. For example, there are considerably more >5% revisions in Estimote than the sell-side. Therefore, similar to how we compute earnings surprise, we normalize earnings revision by share price to produce a more robust revision measure called ENRP (Earnings Revision Normalized by Price):

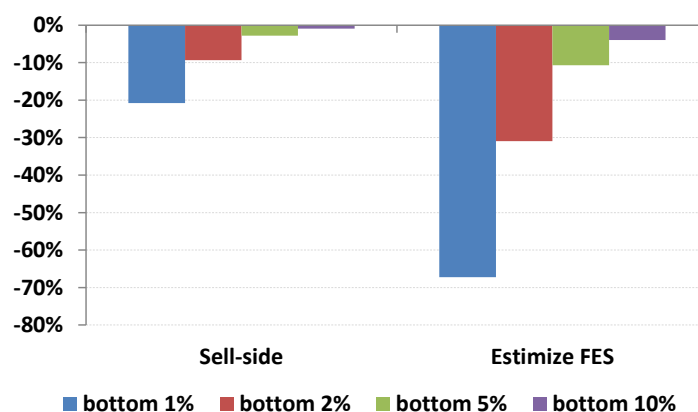
$$ENRP_{i,t} = \frac{EPS_{i,t} - EPS_{i,t-1}}{|Price_{i,t}|}$$

Figure 23 Percentage of EPS changes in the week before earnings announcement

A) Most positive EPS revisions



B) Most negative EPS revisions



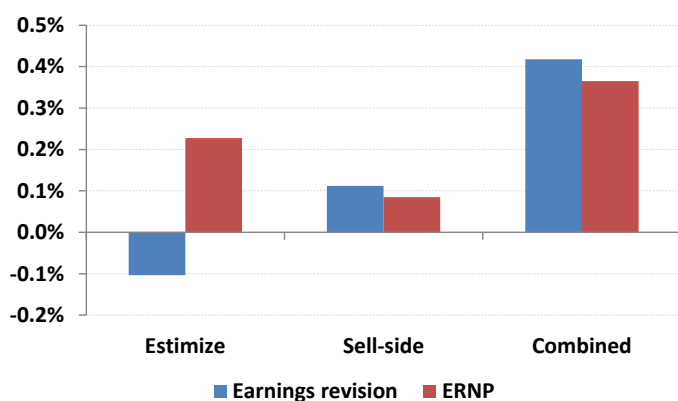
Sources: Estimate, IBES, S&P Capital IQ, FTSE Russell, Thomson Reuters, Wolfe Research Luo's QES

Comparing traditional earnings revision and ERNP, Figure 24 clearly shows the robustness of our new ERNP measure:

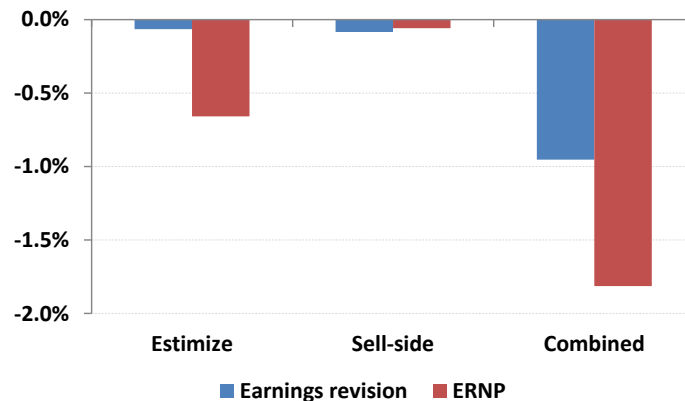
- The excess earnings announcement day return is more consistent based on ERNP than the one based on traditional earnings revision.
- The alpha is significantly larger based on the Estimate data than the one based on the sell-side consensus.
- Combining Estimate and the sell-side further improves performance.
- The alpha on the short side is substantially larger than the long side, especially for the Estimate data. The short-side alpha based on the sell-side is minimal, which reflects sell-side analysts' inability to identify short opportunities ahead of earnings releases.

Figure 24 Average excess earnings announcement day return

A) Top 5% earnings revisions and ERNP



B) Bottom 5% earnings revisions and ERNP



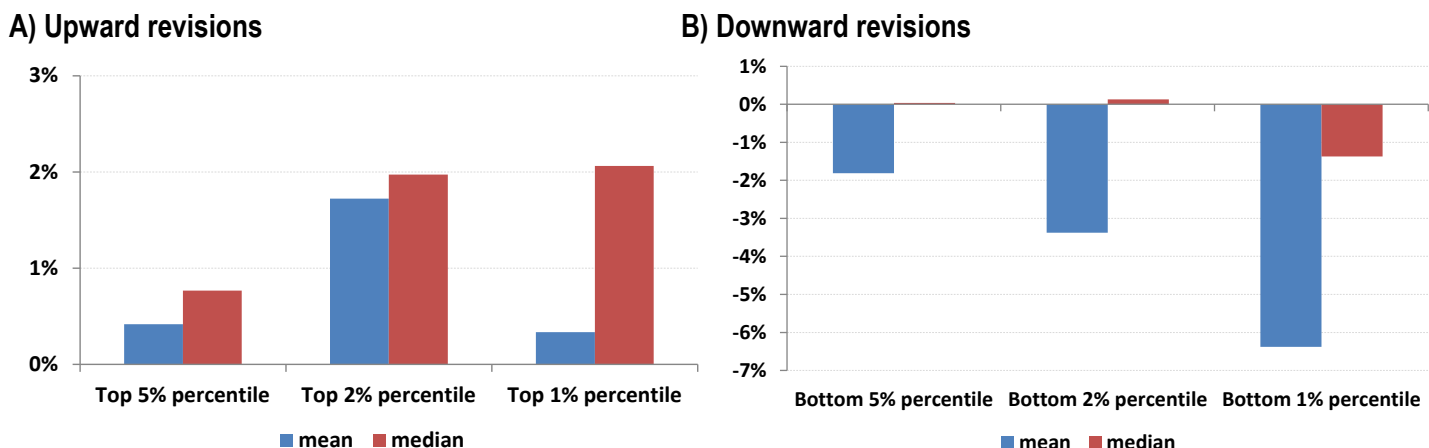
Sources: Estimate, IBES, S&P Capital IQ, FTSE Russell, Thomson Reuters, Wolfe Research Luo's QES

Finally, let's introduce our recommended strategy on trading prior to earnings announcement day. Basically, we would buy (sell/short) those stocks with the highest positive (negative) revisions by both the Estimote and the sell-side consensus right before the earnings announcement day. Revisions are computed on the changes in EPS from the previous week.

Figure 25 shows the excess return on the earnings announcement day, based on our strategy. We note a few interesting observations:

- The average alpha increases monotonically, as we raise the conviction threshold.
- The excess return is skewed on the short side, especially at the extreme levels. For example, as shown in Figure 25 (b), at the -2% level, the median alpha is of the opposite direction from the average excess return. A few very negative returns drag the average alpha down to the negative territory, but slight more than half of the stocks with -2% negative revisions deliver positive returns.

Figure 25 Alpha on earning announcement date



Sources: Estimote, IBES, S&P Capital IQ, FTSE Russell, Thomson Reuters, Wolfe Research Luo's QES

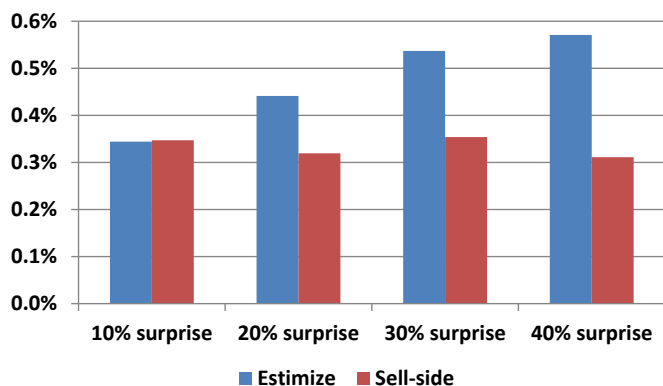
POST EARNING ANNOUNCEMENT DRIFT (PEAD)

We have done extensive studies on the PEAD (Post Earnings Announcement Drift). The behavioral argument is that investors tend to underreact to earnings news; therefore, in the weeks post earnings announcement, stock price tends to follow the same direction as the announcement day return. For example, if a company releases very positive (negative) earnings, not only the stock jumps (plunges) on the announcement, but also the price continues to move up (down) in the following weeks. PEAD is well documented in academia. However, PEAD decays quickly and disappears in a matter of days in the US market, possibly due to arbitrage.

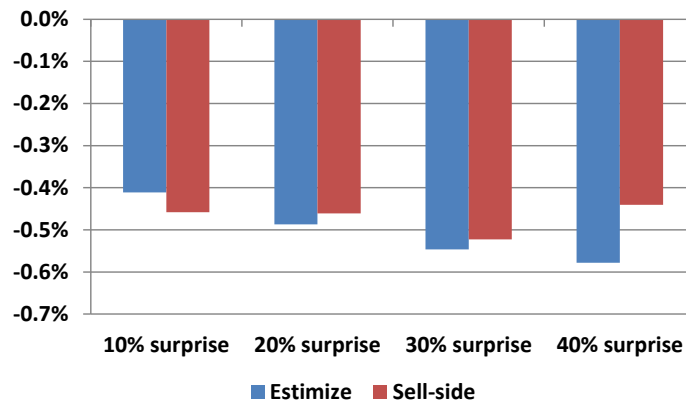
Figure 26 shows the first day PEAD, after a company beats or misses earnings. Since earnings are mostly announced after market close, we define the first day return as the return between the open price to close price after the earnings announcement. This is the maximum possible return that investors could capture. In practice, the actual alpha is likely to be much smaller, because the liquidity at the open is normally small. Nonetheless, Estimote data shows a much larger alpha and a more monotonic pattern than the sell-side consensus.

Figure 26 First day PEAD

A) Positive earnings surprise



B) Negative earnings surprise

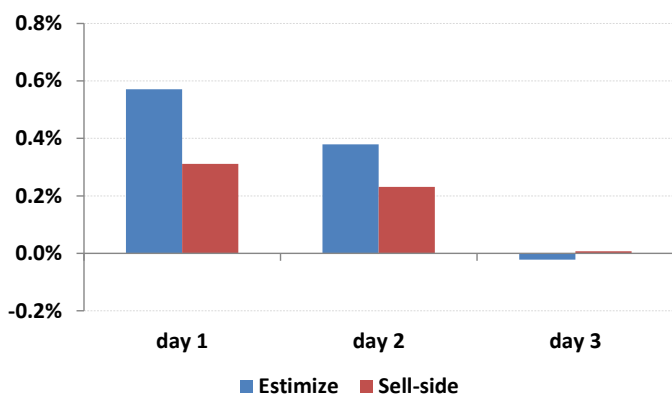


Sources: Estimize, IBES, S&P Capital IQ, FTSE Russell, Thomson Reuters, Wolfe Research Luo's QES

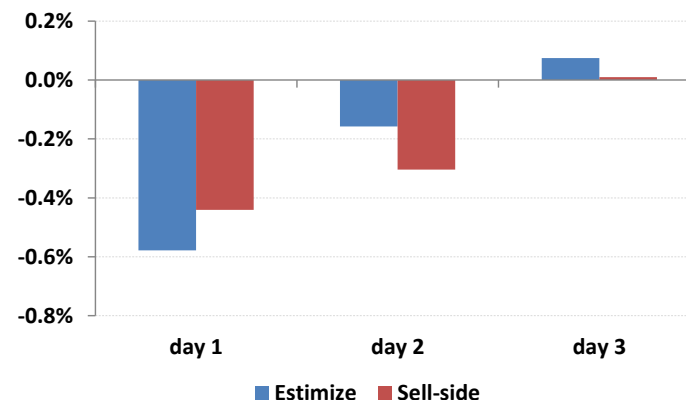
PEAD decays quickly. Even for the largest earnings surprises ($> 40\%$ and $< -40\%$), the PEAD disappears after two days (see Figure 27). In all occasions, it is far more profitable to trade PEAD based on the Estimize data than the sell-side consensus.

Figure 27 Post earning drift decays quickly

A) Excess return when EPS beats over 40%



B) Excess return when EPS misses over 40%



Sources: Estimize, IBES, S&P Capital IQ, FTSE Russell, Thomson Reuters, Wolfe Research Luo's QES

LOW RISK STRATEGIES

Classic finance theory suggests that risky assets should earn higher returns to compensate investors who are willing to take on the extra risk. Empirically, however, we have found the low risk anomaly to be fairly robust in all asset classes (equity market, country, sector, fixed income, etc.) and over time, in that low risk assets deliver higher returns than risky securities. In our previous research, we observe the low risk anomaly in a number of ways to define risk, e.g.,

- Beta

- Realized volatility
- Options-implied volatility
- Idiosyncratic volatility
- Informed trading (using residual probability of informed trading from tick-and-quote data)
- Earnings dispersion

The volatility is usually high on the earnings announcement date. Intuitively, those stocks with high earnings dispersion should have an even higher volatility. We define EPS dispersion for a given stock at a time as the cross-sectional dispersion of EPS estimates from all analysts, normalized by share price:

$$EarningsDispersion = \frac{StdDev(EPS_{i,t})}{Price_{i,t}}$$

As shown in Figure 28, high dispersion stocks (the top half) deliver higher volatilities and lower returns on the earnings announcement day, regardless whether we use the Estimote data or the sell-side consensus. Therefore, removing high dispersion stocks before the earnings announcement date should not only reduce volatility, but also boost returns.

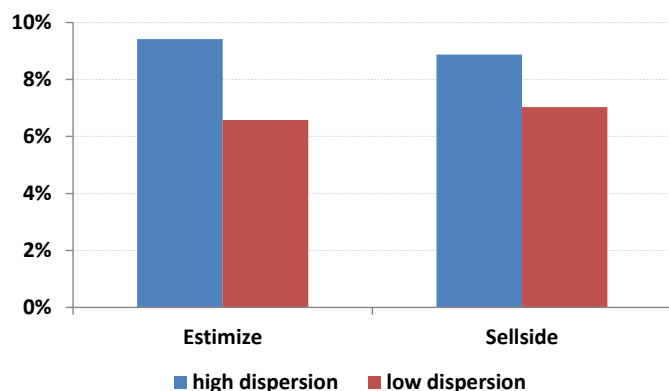
To show the benefit of adding a low risk overlay to a traditional long-only portfolio, we compare the performance of three strategies:

- **Benchmark.** Our benchmark is a market cap weighted long-only portfolio of all stocks in the Estimote universe. Given that the Estimote database has over 1,000 stocks on average, our benchmark is a proxy of US large cap universe (e.g., Russell 1000 index).
- **Low risk portfolio avoiding earnings risk.** In the first low risk portfolio, we exclude all stocks with a pending earnings announcement, one day before the announcement date, from the benchmark.
- **Low risk portfolio avoiding earnings uncertainty.** In the second low risk portfolio, we remove only those stocks in the top half dispersion by either the Estimote or the sell-side.

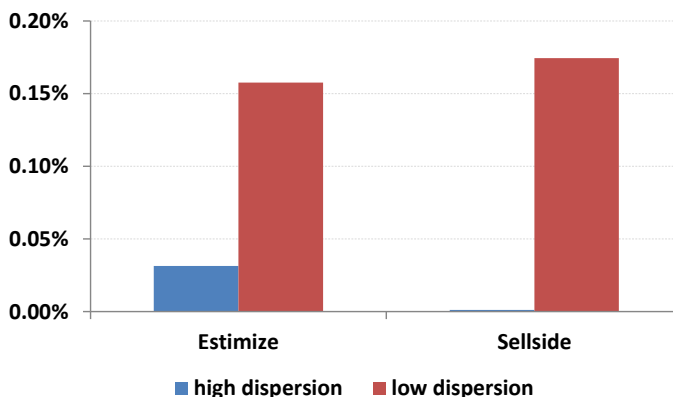
As shown in Figure 29, both low risk portfolios beat our benchmark. Moreover, avoiding high earnings uncertainty boosts the performance even further. In addition, as shown in Figure 30, shunning away from high dispersion names lifts Sharpe ratio and lower portfolio volatility.

Figure 28 High dispersion names have higher volatilities and lower returns on the announcement day

A) Volatility on the announcement date

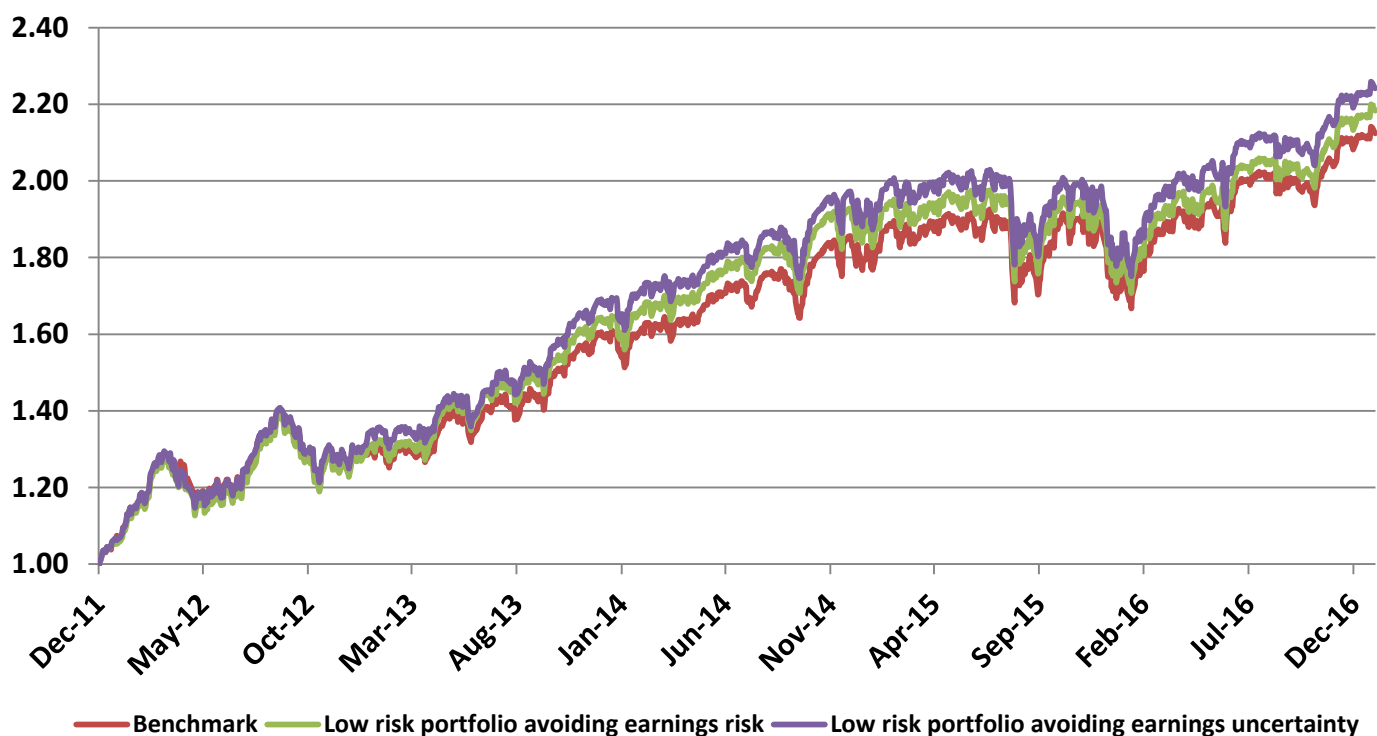


B) Average return on the announcement date



Sources: Estimize, IBES, S&P Capital IQ, FTSE Russell, Thomson Reuters, Wolfe Research Luo's QES

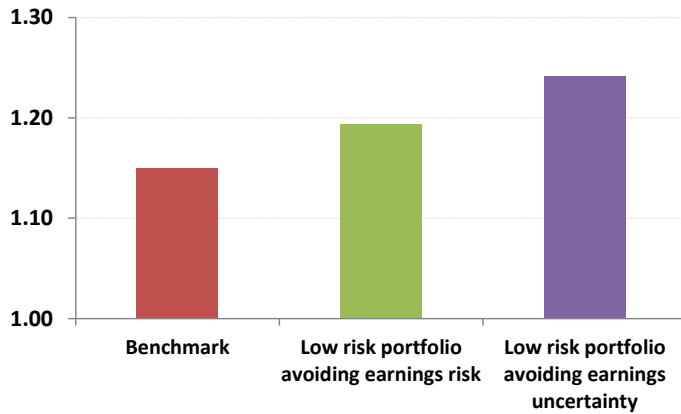
Figure 29 Performance of market cap weighted Estimize universe with and without high dispersion names



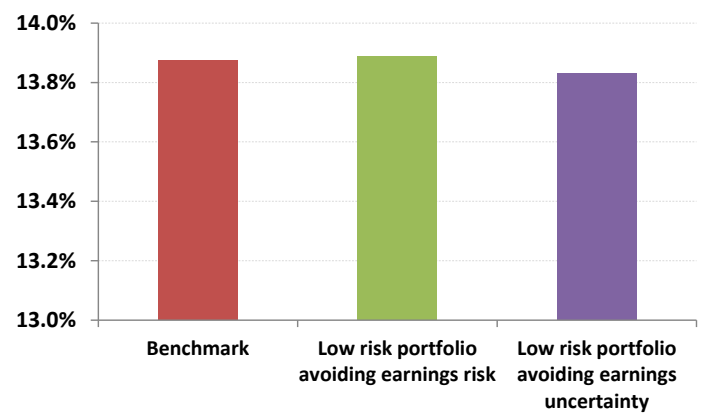
Sources: Estimize, IBES, S&P Capital IQ, FTSE Russell, Thomson Reuters, Wolfe Research Luo's QES

Figure 30 Sharpe ratio and volatility of the long only strategy

A) Sharpe ratio



B) Annualized volatility



Sources: Estimote, IBES, S&P Capital IQ, FTSE Russell, Thomson Reuters, Wolfe Research Luo's QES

LONG TERM INVESTMENT STRATEGIES

Given the timeliness and accuracy of the Estimize data, it is possible to improve any traditional factors that depend on earnings, e.g., earnings yield, earnings growth, ROE, etc.

ENHANCED EARNINGS YIELD

To measure the contribution of more accurate and timelier earnings estimates from Estimize, we compare three earnings yield factors, based on the next fiscal quarter expected EPS:

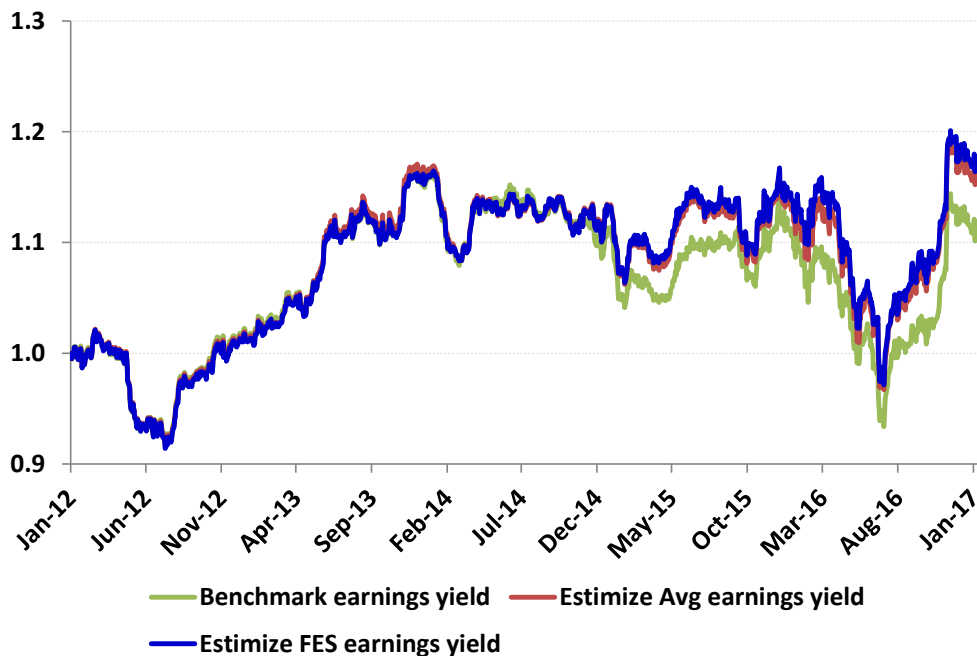
$$\text{EarningsYield} = \frac{\text{FQ1 EPS}}{\text{Price}}$$

The difference among the three factors is on how to compute FQ1 EPS:

- **Benchmark earnings yield.** For the benchmark factor, we use the consensus sell-side EPS, by taking a simple average of CIQ and IBES.
- **Standard Estimize earnings yield.** In this case, we replace the sell-side consensus with the Estimize estimates when we have at least three contributors in the Estimize database.
- **Estimize FES earnings yield.** Instead of replacing with the standard Estimize estimates, we use the FES model introduced in the previous section. As a reminder, the FES model reflects the freshness of each estimate, analyst experience, and analyst skill.

As shown in Figure 31, adding Estimize data clearly improves the performance of a traditional earnings yield factor. Accounting for the freshness of each estimate, analyst experience and skill further boosts returns.

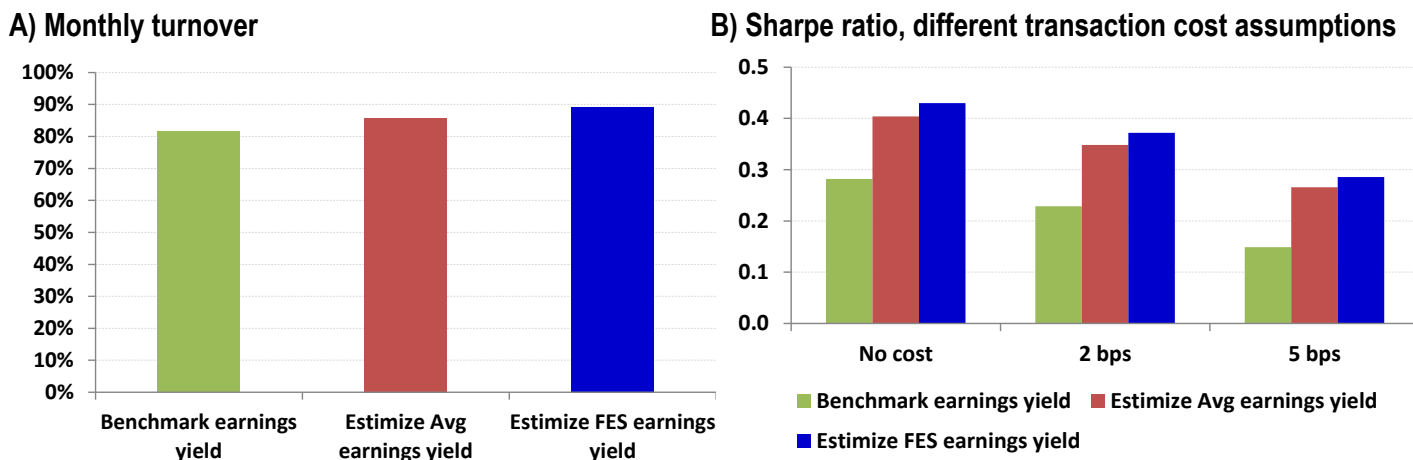
Figure 31 Cumulative performance of different earnings yield factors, long/short quintile portfolio



Sources: Estimize, IBES, S&P Capital IQ, FTSE Russell, Thomson Reuters, Wolfe Research Luo's QES

To fully take advantage of the Estimize data, we assume a daily rebalance in the previous simulation. The turnover of the strategy is relatively high compared with a more traditional value factor (see Figure 32 A). However, even after transaction cost, the Estimize standard and FES factors still outperform the benchmark earnings yield strategy relying only on the sell-side consensus (see Figure 32 B).

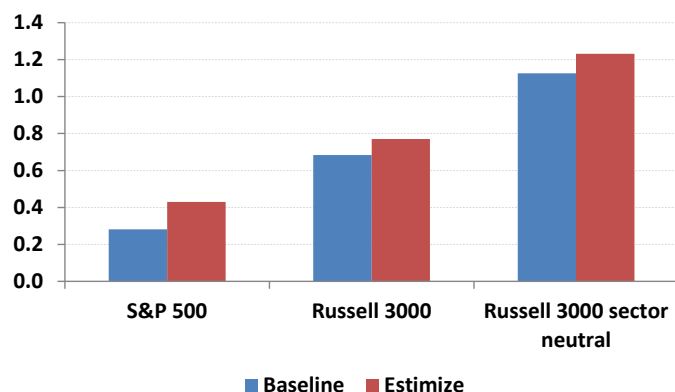
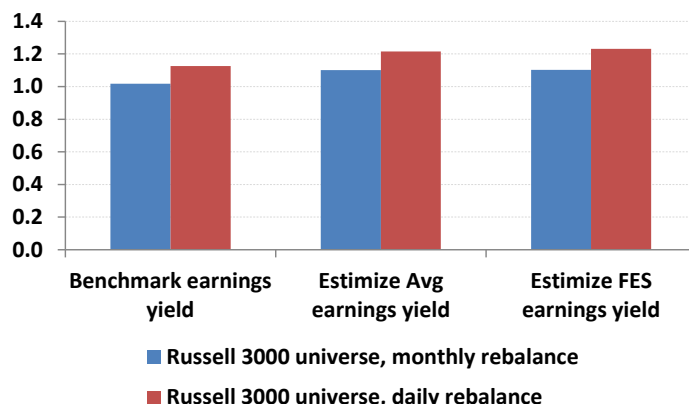
Figure 32 Portfolio turnover and the impact of transaction costs, long/short quintile portfolio



Sources: Estimize, IBES, S&P Capital IQ, FTSE Russell, Thomson Reuters, Wolfe Research Luo's QES

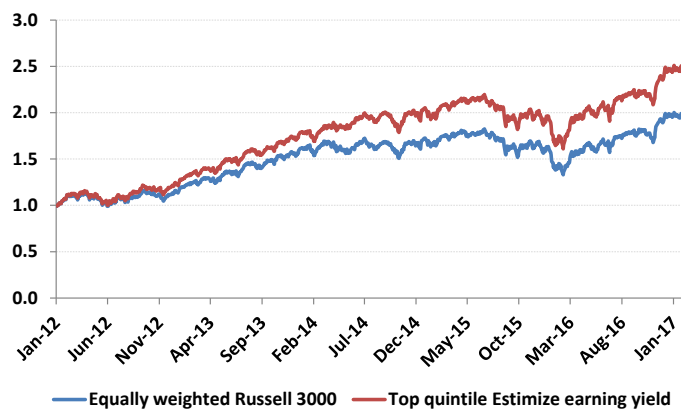
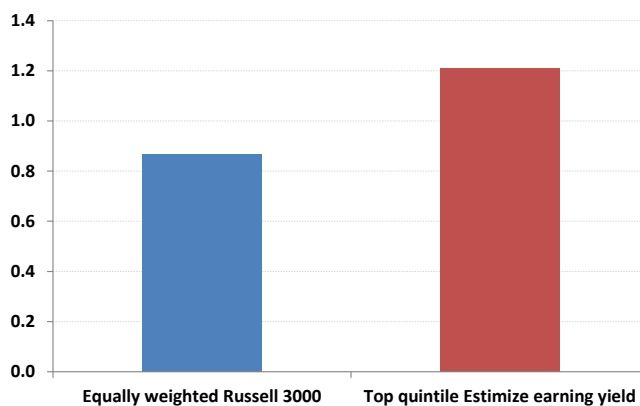
Despite of the slightly large-cap tilt of the Estimize database, the performance of our enhanced Estimize FES earnings yield factor also adds decent alpha in the Russell 3000 universe (see Figure 33 A). Obviously, the improvement is more significant for the large-cap S&P 500 universe, where alpha is more scarce (see Figure 33 A). By neutralizing sector impact, we can further improve performance.

In addition, as shown in Figure 33, a more frequent daily rebalance allows us to access timelier information and further boost performance.

Figure 33 Performance comparison, long/short quintile portfolio
A) Sharpe ratio, different universe

B) Sharpe ratio, monthly versus daily rebalance


Sources: Estimize, IBES, S&P Capital IQ, FTSE Russell, Thomson Reuters, Wolfe Research Luo's QES

Lastly, to show the potential benefit to long-only investors, we compare the performance of the top value stocks (i.e., the top quintile stocks with the highest Estimize FES earnings yield) with an equally weighted Russell 3000 index. As shown in Figure 34, the enhanced value strategy delivers consistent alpha in the long term, by boosting the Sharpe ratio by almost 45%.

Figure 34 Long only portfolio performance, Russell 3000 universe
A) Cumulative performance

B) Sharpe ratio


Sources: Estimize, IBES, S&P Capital IQ, FTSE Russell, Thomson Reuters, Wolfe Research Luo's QES

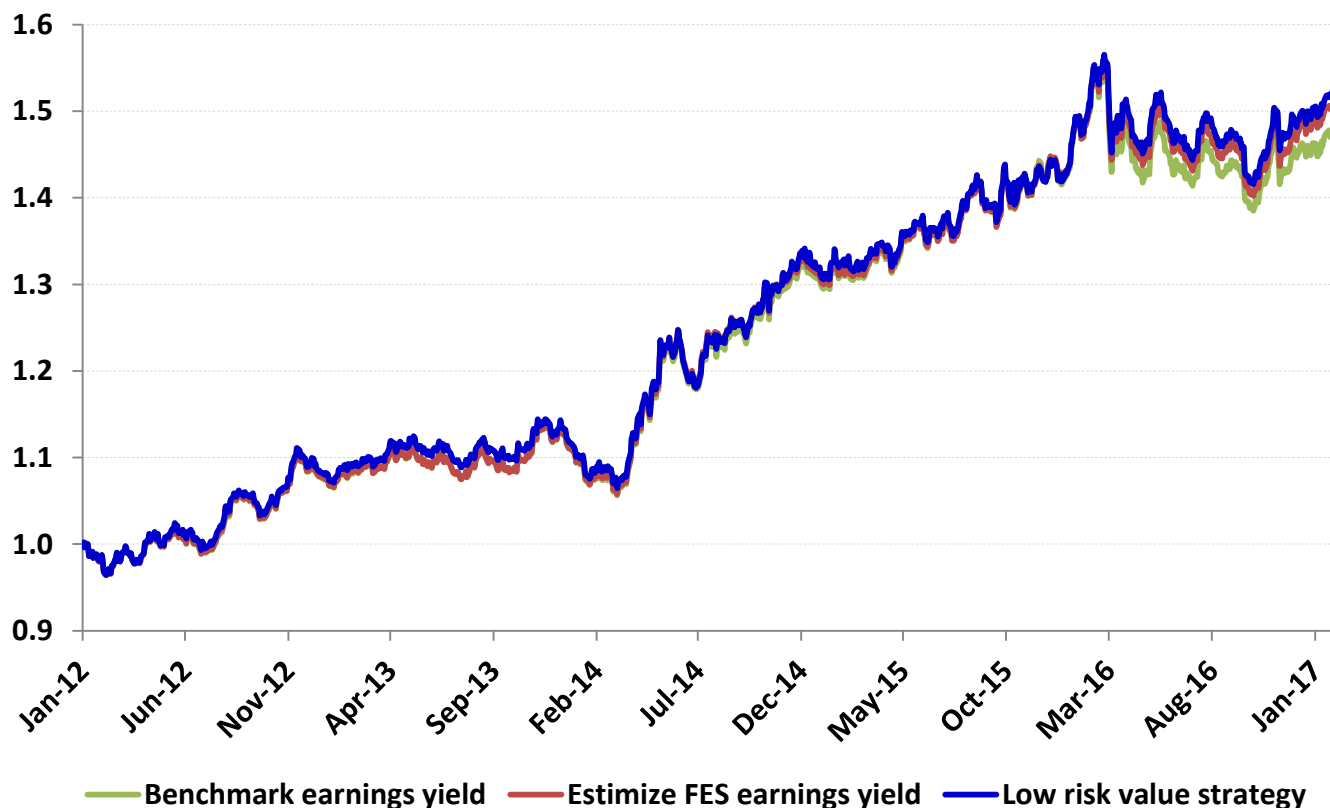
LOW RISK VALUE STRATEGY

Value stocks, on average, are more likely to be those cyclical names that have not been performing well. Indeed, Fama and French [1992] argue that a possible reason why value stocks deliver high returns is to compensate investors for potential distress risk.

As discussed in the previous sections, we show that avoiding earnings risk and earnings uncertainty can lower risk and lift returns. Therefore, combining our enhanced value factor with a low risk overlay should not only reduce portfolio risk, but also capture some diversification benefit.

As a demonstration of a potential low risk value strategy, we further exclude the top half high earnings dispersion names from our Estimate FES value portfolio. As shown in Figure 36, the low risk value factor delivers a Sharpe ratio of 1.25x, with lower volatility than traditional value signals.

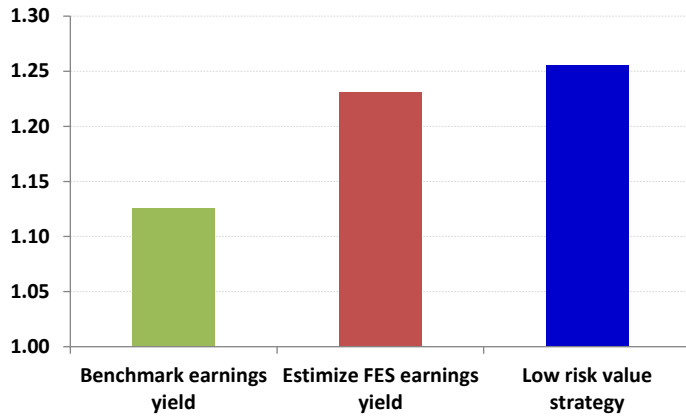
Figure 35 Low risk value strategy performance, long/short quintile portfolio, Russell 3000 universe



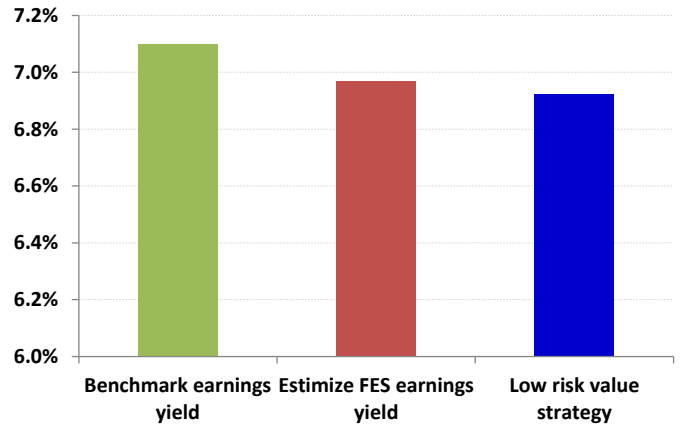
Sources: Estimate, IBES, S&P Capital IQ, FTSE Russell, Thomson Reuters, Wolfe Research Luo's QES

Figure 36 Low risk value strategy performance, long/short quintile portfolio, Russell 3000 universe

A) Sharpe ratio



B) Volatility



Sources: Estimize, IBES, S&P Capital IQ, FTSE Russell, Thomson Reuters, Wolfe Research Luo's QES

BIBLIOGRAPHY

- Batchelor, R., & Dua, P. [1995]. "Forecaster diversity and the benefits of combining forecasts", *Management Science*, 41(1), 68-75.
- Da, Z., and Huang, X. [2016]. "Harnessing the wisdom of crowds", Available at SSRN: <https://ssrn.com/abstract=2731884>
- Drogen, L. , and Jha, V. [2013]. "Generating Abnormal Returns Using Crowdsourced Earnings Forecasts from Estimote", Available at SSRN: <https://ssrn.com/abstract=2337709>
- Fama, E.F., and French, K.R. [1992]. "The Cross-Section of Expected Stock Returns", *Journal of Finance*, vol 47, Issue 2, 427-465
- Jame, R., Johnston, R., Markov, S., and Wolfe, M. [2016]. "The value of crowdsourced earnings forecasts", *Journal of Accounting Research*, 54(4), 1077-1110.
- Johnston, R., Kang, T., and Wolfe, M. [2013]. "Crowdsourcing Forecasts: competition for sell-side analysts", *Journal of Accounting Research*, Spring (2013): 493-522.
- Liew, J. K. S., Guo, S., & Zhang, T. [2016]. "Tweet Sentiments and Crowd-Sourced Earnings Estimates as Valuable Sources of Information around Earnings Releases", *The Journal of Alternative Investments*, 19(3), 7-26.
- Lee, C. M., Ma, P., and Wang, C. [2016]. "The Search for Peer Firms: When Do Crowds Provide Wisdom?", *Harvard Business School Accounting & Management Unit Working Paper*, No. 15-032
- Luo, Y., Jussa, J., and Wang, S. [2017a]. "The Big and The Small Sides of Big Data", Wolfe Research Luo's QES, February 8, 2017
- Luo, Y., Jussa, J., and Wang, S. [2017b]. "Signal Research and Multifactor Models", Wolfe Research Luo's QES, February 16, 2017
- Luo, Y., Jussa, J., and Wang, S. [2017c]. "Style Rotation, Machine Learning, and The Quantum LEAP" Wolfe Research Luo's QES, February 24, 2017
- Nikolic, B., Bliss, B. A., and Kumar, A. [2016]. "Geography, Diversity, and Accuracy of Crowdsourced Earnings Forecasts", Available at SSRN: <https://ssrn.com/abstract=2579402>

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