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Editorial

According to the rational expectations school of macroeconomics, aggregate demand and supply depend not only on inflation but also the public expectation of inflation. There is increasing evidence to show that policies targetted specifically at changing popular sentiment about near term as well as medium term inflation has a compounding effect on the economy's aggregate health. In the first article, authors propose a novel, data driven way to measure such expectations about inflation, leveraging methods from Artificial Intelligence and Natural Language Processing over large news datasets. The second article is a multi-part essay that discusses various valuation technique applicable for start-ups. This will cover various methods of valuation of start-ups from idea stage to public listing. This article looks at valuation of pre-revenue companies. In the third piece, the author explains the prevalent price manipulation in the IPOs through the grey market and concludes that this issue of manipulation should be dealt with more effectively without any hindrance to the normal trading process. The fourth article deals with Ind AS accounting standards and fair value world. The author concludes that financial statements should be viewed through the prism of change in net asset value based on fair value, rather than the current focus on profit and loss/net income. In the last piece, the author looks into the idea of expectations in finance and shows how finance come up with explanations for prices despite the many gaps in our current understanding of expectation formation.

You may send your comments and feedback on this issue to ashok@iimcal.ac.in

Happy reading!

Ashok Banerjee

Crowdsourcing Inflationary Expectations through Text Mining: Do the Pink Papers whisper or talk loudly?

Ashok Banerjee[1], Ayush Kanodia[2], Partha Ray[3]

1. Introduction

How do we know about the general sentiment in the economy? Is it bullish or bearish? This question seems to haunt academicians and policy makers alike. The best way to gauge it is perhaps approaching the public. The general philosophy is best captured in the burden of Kishore Kumar's song of Rajesh Khanna starrer movie *Roti* (1974) that goes, "*Yeh jo Public hai - sab jaanti hai*". The question is: where does one meet the public and how does one listen? Does the public whisper or talk loudly? More importantly, does one get a unified message from such public talk or does all information get drowned in cacophony? This paper makes a preliminary attempt to gauge public opinion in newspaper reports. Within this general philosophy, our attempt in this paper is, of course, more modest. We look into one particular economic variable, *viz*., inflation.

Needless to say, Inflationary expectations tend to play a crucial role in macroeconomic and financial decision / policy making. In particular, it is of paramount importance when monetary policy is conducted within an inflation targeting framework or when the financial market player is thinking of her return from the bond / forex markets. But a perennial question in this context is: how to measure inflationary expectations? Three broad strands are identified in the literature. First, model based forecasts (univariate or multivariate variety) are often taken recourse to. Second, inflationary expectations are also derived from class / group-specific inflationary expectations surveys routinely conducted by central banks / financial data providers. Third, inflationary expectations / perceptions are also inferred from the market yields of inflation-indexed bonds.

While each of these methods is useful, each has its limitations as well. In this paper we propose and adopt a novel method of inferring inflationary expectations using a machine learning algorithm by sourcing economic news from the leading financial dailies of India. In particular, we argue that Economics / Finance can leverage advances in artificial intelligence (AI), natural language processing (NLP) and big data processing to gain valuable insights into the potential fluctuations of key macro indicators and attempt to predict the direction (upward *versus* downward) of monthly consumer price inflation.

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The remainder of this article is organized as follows. While section 2 discusses the motivation of this approach, the methodology is delved in section 3. Section 4 presents the results and section 5 concludes.

2. Motivation and Received Literature

The motivation of this approach can be traced in two distinct strands of literature. First, among the monetary economists there is a large literature of what has come to be known as the "narrative approach to monetary policy". While the origin of this approach can perhaps be traced to Friedman & Schwartz (1972)'s *Monetary History of United States*, Boschen and Mills (1995) derived an index of monetary policy tightness and studied the relation between narrative-based indicators of monetary policy and money market indicators of monetary policy. They found, "Changes in monetary policy, as measured by the narrative-based policy indices, are associated with persistent changes in the levels of M2 and the monetary base". More recently, Romer and Romer (2004) derived a measure of monetary policy shocks for the US. Instead of taking any particular policy as an indicator of monetary policy shock, Romer and Romer (2004) derived a series on intended funds rate changes around meetings of the Federal Open Market Committee (FOMC) for the period 1969–1996 by combining the "information on the Federal Reserve's expected funds rate derived from the Weekly Report of the Manager of Open Market Operations with detailed readings of the Federal Reserve's narrative accounts of each FOMC meeting". But all these papers involve some degree of subjectivity of reading the policy narratives. Hence a key question remains: how does one get rid of this subjectivity? It is here that more contemporary tools of machine learning, nature language and big data processing become helpful.

This second strand of literature comes from machine learning. To get a perspective of its emergence, it is important to note that there has been a healthy scepticism and conscious efforts on the part of the academics to avoid forecasting economic / financial variables. Smith (2018) in a recent article attacked the profession and went on to say:

> "Academic economists will give varying explanations for why they don't pay much attention to forecasting, but the core reason is that it's very, very hard to do. Unlike weather, where Doppler radar and other technology gathers fine-grained details on air currents, humidity and temperature, macroeconomics is traditionally limited to a few noisy variables .... collected only at low frequencies and whose very definitions rely on a number of questionable assumptions. And unlike weather, where models are underpinned by laws of physics good enough to land astronauts on the moon, macroeconomics has only a patchy, poor understanding of individual human behavior. Even the most modern macro models, supposedly based on the actions of individual actors, typically forecast the economy *no better* than ultra-simple models with only one equation ....whatever the reason, the field of macroeconomic forecasting is now exclusively the domain of central bankers, government workers and private-sector economists and consultants. But academics should try to get back in the game, because a powerful new tool is available that might be a game-changer. *That tool is machine learning*" (emphasis added).

But what is machine learning? Loosely speaking, "Machine learning refers to a collection of algorithmic methods that focus on predicting things as accurately as possible instead of modelling them precisely" (Smith, 2018). With rapid advances in storing and analysing large amounts of unstructured data, there is increasing awareness that these data could be a rich source of useful information for assessing economic trends. Various attempts have emanated in forecasting macroeconomic and financial variables. Illustratively, Nyman and others (2016) used the Thomson-Reuters News archive (consisting of over 17 million English news articles) to assess macroeconomic trends in the UK. More recently, using machine learning techniques Shapiro & others (2018) developed new time series measures of economic sentiment based on computational text analysis of economic and financial newspaper articles from January 1980 to April 2015. There is now a burgeoning literature on this issue, thanks to the Rational Expectations thinking that policy making needs to have some sense of the future sentiment / expectations. However, the policy maker needs to take care of the popular adage of Goodhart's law whereby "when a measure becomes the target, it can no longer be used as the measure", so that forecasts fail when used for policy prescription and when used as targets naively.

Detection of sentiment from the newspapers seems to be less prone to this syndrome. Much of this literature asks the machine to find out the recurrence of some key words with appropriate identifiers in the newspaper articles so that the detection does not get corrupted by any subjective bias. Our paper ties to decipher the inflationary sentiment from the newspaper articles.

3. Methodology

Literature on sentiment analysis shows that mere frequency of information arrival (news articles) may not explain change in an economic variable. What drives economic agents is the sentiments (i.e., quality) of information. Extracting sentiment from newspaper reports is one of the major contributions of our paper.

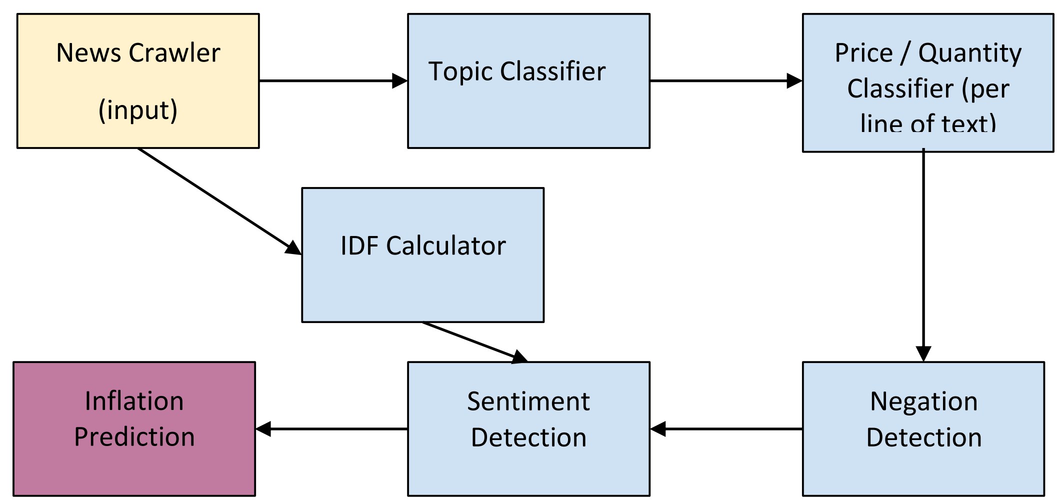
We develop a system over python and several accompanying libraries to access large chunks of newspaper data, parse and process the news content, and make a well founded estimate of the direction of inflation (CPI) in the near (next) month using sentiments generated from news content for the current month.

Input: To forecast inflation for a month (released in the middle of the month), we take as input news from 20th of previous month to 10th of current month. We can take as many newspapers as we like. For instance, for inflation of April 2015 (released an Apr 15), we use news from March 20th 2015 to April 10th 2015. Note that CPI numbers are released in the middle of a month (12th to 18th).

Output: For each month, we consume all the input news content and after processing, produce a single number which denotes the sentiment towards inflation for that month.

Component: Our system consists of the following components arranged in a pipeline.

Figure 1: System pipeline



Our search is limited to news from two business dailies (Economic Times and Business Line). We crawl the news from the "factiva" database online using a python tool. This is our input to the rest of the system.[4] Let us now turn to each of the components of Figure 1.

Topic Classifier

This module takes as input a news article and classifies it into one of the sub baskets used to calculate the overall CPI. The sub baskets are *fuel*, *food*, *cloth*, *housing*, *intoxicants* (alcohol and various tobacco consumables) and *miscellaneous*.[5] The classifier can classify an article into one of these multiple baskets. We manually labelled about 4000 articles for two random months (Nov-Dec 2015 and 2016) to serve as our training set. It is interesting to note that the training dataset included the period of demonetisation.

Price/Quantity Classifier (Per line of text)

This module takes as input a line of text from an article and flags it as talking of price of the commodity, quantity of the commodity, of both, or of neither. Each line is classified into one of four categories - talking of neither price or production, of only price or only production, or both. The idea is that inflation expectation is triggered

[4] We are in the process of extending it to use news from "Business Standard" and "Financial Express".

[5] The relevant weights for each of these groups are 45.86%, 2.38%, 6.53%, 10.07%, 6.84%, and 28.32%, receptively.

by knowledge of either demand pull inflation (higher prices due to higher demand) or cost push inflation (higher prices due to lower supply).

For instance, “Oil prices unlikely to rise” would be classified as talking of only price, “OPEC cuts output on breakdown of talks” would be classified as talking of only production, “While prices seem to be rising, production is not falling commensurately, leading to inventory accumulation” would be classified as talking of both price and production, while “New policies on the horizon” would be classified as talking of neither price nor production.

Negation Detection (Per line of text)

This module takes as input a line of news text and checks whether parts of the line are negated using negation words as “not”, “unlikely”, “improbable” etc. The way it does this is as follows. For example, consider the line: “Oil prices not likely to rise”. The negation detector returns as output “Oil prices <negated scope> not likely to rise <\negated scope>”. The additional markers inform us of the part of the sentence whose adjectives (in this case *rise*) are negated in meaning. This is utilised downstream in sentiment detection (see example in later section on sentiment detection).

IDF (Inverse Document Frequency) Calculator

TF (Term Frequency) of a word is defined as the number of times a word is seen in an article (document). IDF of a word is defined as a measure of the salience (or contribution to new information) of a word, based on how likely the word is to appear as a prior. If we merely use Term Frequency, we would not account for the fact that words which have a high prior of occurring will bias our estimate. For instance, determiners like *a*, *the*, will have naturally high TF, and they need to be downweighted.

This module looks at sentiment words (generally adjectives) which we use downstream to infer sentiment from news articles, and calculates their IDF (Inverse Document Frequency) over our news articles dataset. Hence, for a word which appears in every document, IDF is zero, whereas it is most for a term which occurs in only one document.

Our IDF is calculated based on the news articles for the first six months of our dataset (months of July-December 2015). This should have broad enough coverage to give us a principled and correct estimate of IDF.

Sentiment Detection

This module takes as input an article, and rates each line of text in the article with a number which describes whether the line indicates a rise or a fall in inflation. For this, it uses the information inferred upstream - whether the line talks about price/production, its negated scopes, and the relative strengths of sentiment adjectives. Sentiment adjectives which appear closer to the mentions of price/production are weighted more.

Illustratively, consider the sentence “Oil prices not likely to rise”. As explained earlier, this sentence is classified as talking of price (due to the word “*prices”)*. Consider the IDF of rise to be 2.0. Consider the dampening factor for interword separation between the adjective (*rise)*and subject (*prices)*to be 0.8. We exponentiate the dampening factor to the number of words in between, which is 3 in this instance*(not likely to)*. Therefore, our sentiment score is (0.8^3)*2=1.024. However, the sentence adjectives are negated as determined by the output of the Negation Detection module ("Oil prices <negated scope> not likely to rise <\negated scope>"). Therefore, the value for rise is negated to -2.0, and we end up with a sentiment score of -1.024

After scoring each line, the article sentiment score is simply a weighted sum of the scores for the individual lines. It strongly attributes more weight to the headline and line towards the beginning of the article. This method provides an unscaled number (which takes all real values, but is likely in the range (-10, 10) which determines the strength (and direction) of sentiment of each line in the article. We dampen this unscaled number to a number between (0, 1) (exclusive), using a dampening function function. The higher the number, the more it indicates a positive sentiment towards a rise in inflation.

Inflation Prediction

We follow a short-term prediction approach with monthly updation of parameters. We use individual sentiment values for each article in a month, and aggregates them into a single predicted inflation number for the next month.

We learn a multivariate regression model over our training months, which is as follows:

$$I(t) = k + aS_{food}(t-1) + bS_{fuel}(t-1) + cS_{cloth}(t-1) + dS_{misc}(t-1) + eS_{general}(t-1) + fI_{dm}$$

I_{dm} is an indicator variable which is 0 for all months before demonetization and 1 afterwards. This is to inform the model that an external event, which affects public sentiment strongly, has occurred. We note that the introduction of this variable results into a significant improvement in our prediction model. We may introduce such variables for other similar external shocks to the economy, which strongly affect inflation. $I(t)$ is Inflation at time t (month t), and $S_x(t)$is sentiment for basket 'x'.

We predict inflation for month i, using the sentiments and inflation figures of month i – 1. Similarly, for month i + 1, we use the actual inflation number for month i, so that our model is improved.

Input Size

Per newspaper, there are about 50 articles per day. That adds up to 1500 articles per month per newspaper. We currently work with two newspapers (*Economic Times* and *Business Line*), therefore we have around 3000 articles per month (Table 1).

Table 1: Summary statistics for number of articles in each component of CPI				
Topic	Mean	Median	Min	Max
Fuel	108	100	38	234
Food	149	138	94	239
Cloth	30	29	13	48
House	71	73	40	132
Pan and intoxicants	6	6	1	15
Miscellaneous	337	338	236	446
General	6	5	0	22

Each sub basket component of CPI has about 5 - 400 articles per month. The *general* category is not a CPI component, but we measure sentiment as belonging to this category if an article directly addresses inflation (and does not talk of any of the subcomponents of the CPI basket). This serves as a useful signal to measure sentiment towards overall inflation.

As a rough estimate, *misc* contains the most number of articles per month at 350 - 400 on average, and the other baskets contain 50 - 250 articles per month on average. There are very few articles (about 7 on average) per month addressing the *general* category.

4. Performance Metrics and Results

It takes about 60 - 120 seconds of real time on a commodity PC to process an entire month's news and output the sentiment score for the month. The configuration used is an i5 2.30 GHz processor, with 2 cores and 2 threads per core (although at present we do not use multithreading). Our system is built in python and these measurements were made on Linux. We should note that this is unoptimized code, so within python itself, optimizing should lead to faster performance. Further, using a lower level language and libraries should lead to even faster performance. There is great scope for parallelization in our system, since each article is processed independently of the other. Leveraging this could lead to orders of magnitudes improvements too.

We calculated monthly sentiment for each of the CPI baskets and performed a univariate regression of basket sentiment on basket inflation. We found high univariate correlation for the *food*, *fuel*, *cloth* and *misc* baskets, as well as high correlation between sentiment for the *general* category and overall inflation. The results are given in Table 2.

Table 2: Univariate Regressions of each components of CPI

(General form: $I_i(t) = k + a\,S_i(t-1)$; for i = food, fuel, cloth, misc, general)

	coefficient	coefficient values	Standard errors	t_values	probabilities
Food	k	0.43	1.07	0.40	0.69
	a	0.4797	0.068	7.099	0.0
Fuel	k	2.44	0.598	4.076	0.0
	a	0.2326	0.040	5.842	0.0
Cloth	k	5.25	0.720	7.29	0.00
	a	0.8382	0.25	3.42	0.00
Misc	k	2.40	0.75	3.187	0.002
	a	0.16	0.041	3.801	0.00
General	k	5.17	0.51	10.11	0.00
	a	0.42	0.17	3.56	0.001

Further, the multiple regression leads to a high significance for fuel, food as well as general sentiments. Table 3 reports the regression results.

$$I(t) = k + aS_{food}(t-1) + bS_{fuel}(t-1) + cS_{cloth}(t-1) + dS_{misc}(t-1) + eS_{general}(t-1) + fI_{dm}$$

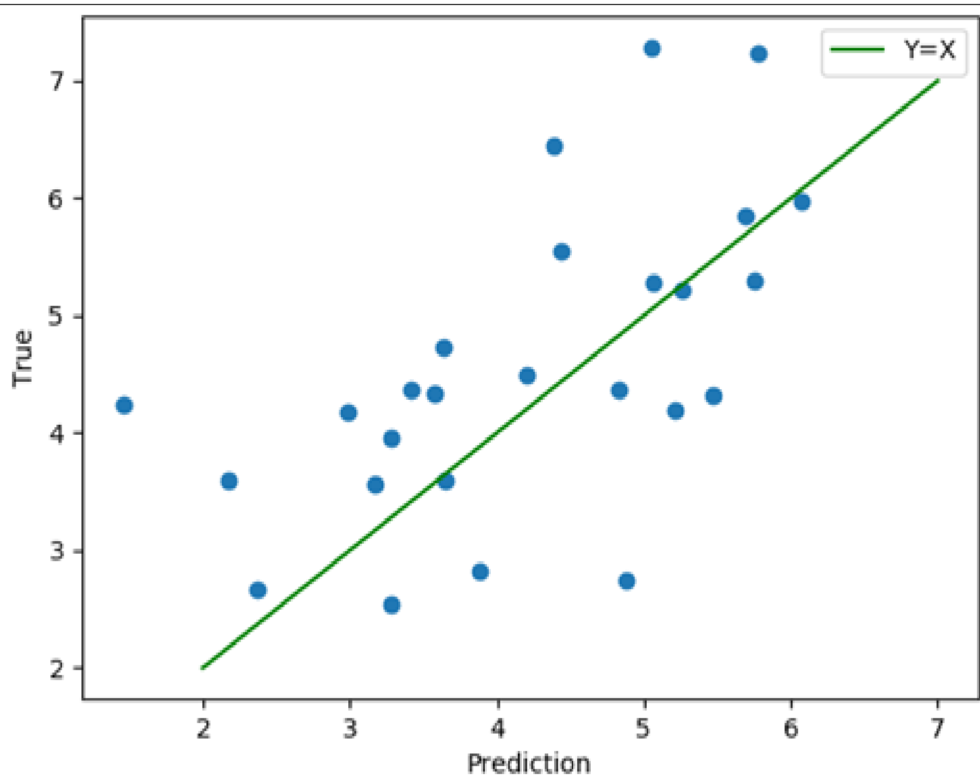
$I\,(t) = k + aS_{food}\,(t-1) + bS_{fuel}\,(t-1) + cS_{cloth}\,(t-1) + dS_{misc}\,(t-1) + eS_{general}\,(t-1) + fI_{dm}$

Table 3: Projecting General CPI Inflation: Base line Regression				
coefficient	coefficient values	Standard errors	t_values	probabilities
k	2.1106	0.849	2.486	0.015
a	0.0848	0.041	2.071	0.042
b	0.2377	0.048	5	0
c	0.176	0.179	0.986	0.328
d	-0.0588	0.051	-1.147	0.255
e	0.1697	0.084	2.023	0.047
f	-2.2455	0.463	-4.851	0

Prediction Results

How is the predictive performance of the model we have developed? The figure below charts a scatter plot of true inflation *versus* predicted inflation using our model. We achieve a correlation score of 0.59.

Figure 2: Inflation (True *versus* Predicted)



5. Concluding Observations

Measuring inflation expectation is a key component of economic and financial policy making. We use text mining to predict inflation expectations. This experiment of investigating whether inflation perception can be measured using newspaper text essentially consists of two sub experiments. The first is to check how well an automated system, when invoked on a single newspaper article, can infer its general sentiment about inflation. This is to say that if an expert (economist) were to read the same article and conclude that this article says price is going to rise, the system should be able to provide the same result. The second is to check whether given such sentiments about each article, does the aggregated sentiment from the monthly news remain significant and relevant to predict actual inflation numbers.

The first of these subtasks, we must say, has achieved high accuracy. When we evaluated the sentiment inferred by the system on individual articles by hand, the system performed accurately almost all the time, and even corrected the human labeller on some occasions! To this extent we believe that the underlying Natural Language Processing used to generate such sentiment may not benefit much from improvements, as our “simple” model appears to do well. The most significant way to improve this now could be to target a finer level of granularity in terms of inferring article sentiment. That is to say, the challenge is to build a system which not only tells us whether price is going to rise or fall, but also by how much. Note that this task is indeed hard for even an expert to complete.

The second of these subtasks however, may see various improvements. For one, we have yet only observed (largely) direction of sentiment of an article. However, if the article talks about something relatively unimportant, we may wish to discount its contribution to overall sentiment. This may be based on the commodity it is talking about, its source, the tense of the text, and the timing of the article (within our prediction horizon which is monthly), none of which we have yet included in our model. Future work in this direction may aim to incorporate such factors.

One of the principled limitations of our approach is that in a developing country like India (versus say, the United States), financial news often does not percolate (fast enough) to the rural population. Hence, using only financial news sentiment to measure perception towards inflation may not be good enough. To this end, we performed our predictions (as above) on urban inflation instead of overall inflation, and saw a slight improvement in results.

Of course, one of the crude ways to improve our system further would be to use more newspapers, and to use more labelled data. We could also include other measures of public sentiment for inflation, in the form of well-read blogs, news published by the central bank in press releases, and even social media data such as twitter posts.

This is a novel, if not the first attempt, to quantify public sentiment towards inflation by inferring it from newspaper text for India. Besides, it compares well with the IESH (Inflation Expectation Survey of Households) conducted by the RBI in order to measure inflation perception as IESH achieves a correlation coefficient of 0.50

in predicting the actual inflation figure, whereas we obtain 0.59 with our method. We hope that such approaches to predicting macroeconomic variables are investigated further by the research community, and fruitful results applied in public policy making.

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Valuation of Start-ups: Part II

Ashok Banerjee

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This issue deals with valuation of pre-revenue companies. We define a pre-revenue company as one, which has already completed prototype and obtained customer validation. The company may or may not have some revenue. The fact that the company has produced prototypes/proof of concept implies that ideation stage is over and customer validation further demonstrates that the product/service will have commercial acceptability. Investment at such an early stage is highly risky. Therefore, angel investors at this stage will only seek scalable investments-companies that can grow revenues very fast within five to eight years. The potential to scale up operations at a greater pace in early years depends solely on the quality of founders and the leadership team.

There are two popular methods to evaluate a pre-revenue company: *the scorecard method* and *the venture capital method.*

The Scorecard Method

This is a qualitative framework to evaluate fundability of a start-up that has no or a few small-ticket customers. At this stage of a start-up, it is impossible or futile to judge its viability on the basis of financial projections. The scorecard method, therefore, relies on broad factors that are essential for the success of a business plan. This method tries to raise relevant questions to evaluate size, scalability and sustainability of a business. The questions posed should be as objective as possible so that a score can be assigned to each question. Decision to fund a start-up at this stage depends on the overall score obtained. A prospective investor may have a threshold score to fund any early stage start-up. Start-ups securing a higher score would have greater probability of funding.

An early-stage investor evaluates a pre-revenue company on the basis of the following criteria: (a) strength of the management team; (b) size of the market opportunity; (c) level of competition; (d) implementation plan; and (e) funding required. Each criterion will have weights ranging from highest (25-30%) for the management team and lowest (5-10%) for funding requirements. An investor will design several questions for each factor (criterion) and assign marks/scores. For example, founder's experience and willingness to step aside for a new CEO, if necessary, could be important questions to evaluate strength of the management team. Often an inventor may be the bottleneck for scaling up of operations. The innovator may have great knowledge of the product but very little idea about how to run an organisation or even how to take the product to the market. In such a situation, any prospective investor may insist that the funding may be conditional on the founder's willingness to handle over the operational responsibility to a professional CEO. If the founder is unwilling, that may turn out to be a deal killer. On the other hand, if the founder voluntarily makes such a transition a key part of the business plan, the investor will be impressed and put a higher score. Similarly, size of the specific market and potential revenue in five years could be relevant questions for understanding the size of the market opportunity. If the market opportunity is small, no investor may be interested in the business even if it has a great team and product.

Table 1: Illustrative Scorecard

Criteria/Factor	Weight (%)	Remarks
Management Team	25-35	Founder's experience, completeness of the team, possibility of hiring a CEO
Market Opportunity	15-30	Size of the market, expected revenue of the company in N years
Level of Competition	10-20	How many competitors, strength of competitors, barrier to entry, patent/copyright
Implementation Plan	5-15	Stage of business- prototype or proof of concept validated? How many users?, Sales channel
Funding required	5-10	How much funding is required?

If the product or service is patentable and the founders have obtained necessary patent, it increases the entry barrier. A higher entry barrier would reduce competition in early years of the venture and such a start-up should be able to attract funding. Implementation plan of the business should be unambiguous and actionable. An important factor at this stage is to identify sales channel that can support the projected growth. If product facilities are required, the founder should be able to clearly state whether production will be outsourced and vendors are identified. If production were to be done in-house, a related question would be whether land is available and how long will it take to build the production facilities. In the early stage, investors prefer that manufacturing is outsourced so that funding requirement is moderate. Finally, if the ask for fund is high at pre-revenue stage, chances of getting positive response from prospective investors are remote. Funding up to $1 million may be available at this stage if the overall score is high. If the requirements for fund are higher, it is quite difficult for a start-up with no revenue to generate enough interest among early-stage funders.

The Venture Capital Method

The venture capital (VC) method is an optimistic method, which only considers successful scenario of a business. It is used at a stage where the start-up has clocked some revenue to demonstrate that its product/service has market acceptability. The VC method assumes that the start-up, it is considering for funding, will be successful. It asks the entrepreneur to predict the revenue of the business at the end of five or seven years. It, therefore, assumes that the business will survive till such time and would generate the target turnover. Of course, the entrepreneur will have to justify the projected revenue and the investor would ensure that the number is not too optimistic. Typically, at pre-revenue stage, entrepreneurs show non-linear growth in revenue in early years on the assumption that necessary funding will be available and the management team would have the capacity to manage such significant growth rates.

Once the projected revenue is estimated, the VC method requires two more variables to arrive at the post-money valuation- the revenue multiple and an appropriate discount rate. Post-money value refers to the value of the firm assuming the enterprise receives the required funding. If one deducts the investment from post-money value, one gets pre-money value. The value of a firm in VC method with an exit after N years is given by :

Enterprise Value= [Projected Revenue at the end of year N * P/S Multiple]/(1+IRR)^N

The *revenue multiple* should be chosen in such a way that a fair value can be obtained. Here, the funder has to decide about an appropriate multiple. This would involve identifying comparable firms and their revenue multiple at present level. For example, if the start-up is an online food delivery service company like Swiggy, and Zomato, one needs to obtain the revenue multiple at which these start-ups have raised money recently. Swiggy's revenue in FY 2017 was reported at Rs. 133 crore versus Rs. 20 crore in FY 2016- registering a phenomenal growth in top line. Swiggy had raised $80 million in May 2017 at a total valuation of $400 for the company. If one uses the FY2017 turnover of Swiggy, this valuation implies a staggering Price-to-sales (P/S) multiple of 195! Swiggy has further raised $100 million almost a year later (February 2018) at a valuation of $600 million. So, the revenue multiple has gone up in anticipation of even a higher revenue growth in FY 2018. It is interesting to note that even when revenue grew by six times for Swiggy in FY 2017, losses too grew by 50% to Rs. 205 crore. It is clear that investors at early stage of a start-up fund growth and are not bothered about profitability. Swiggy's competitor, Zomato, raised $200 million at the same time (February 2018) when it reported overall revenue for FY 2017 of Rs. 333 crores (81% more than last year) and revenue from online ordering of Rs. 58 crore (eight-folds higher than previous year). Zomato raised the latest round at a valuation of $1.1 billion resulting in a sales multiple of 21. Later Morgan Stanley[6] raised the valuation of Zomato to a whopping $2.5 billion on the basis of expected revenue of Zomato of $65 million in FY 2018, implying a revenue multiple of 38. Another related start-up, Grofers (online grocery), has recently raised $61.3 million at an enterprise value of $300 million[7] and reported an annual turnover of Rs. 1000 crore ($154 million). This implies a modest P/S of 2. Possible reason for such a low multiple could be the fact that Grofers was struggling for the past two years with its business model and witnessed more than 30% drop in its valuation. Two important lessons from the story of these three start-ups are: (a) there is a great deal of optimism with these start-ups in view of such high P/S multiples; and (b) the variation of the multiples is huge. Such wide variations make it difficult for an investor to use these numbers as benchmarks to value any pre-revenue start-up in the same sector. So, what should be an appropriate P/S multiple for a pre-revenue start-up given the two recent success stories of Swiggy and Zomato? Will the pre-revenue company be able to generate levels of revenue growth shown by these two start-ups in five years? If the answer is affirmative, one can use a conservative P/S multiple, which is about 30 (closer to Zomato). One may note that Zomato has achieved the present multiple after ten years of struggle. If the answer is in the negative, one may use P/S multiple of listed comparable firms, if available.

The *preferred discount rate* (also known as internal rate of return) of the investor should take into account the following four factors: (a) time value of money (as the exit from early stage investment is prolonged, it is essential that one uses yield of long-term government bond for this purpose); (b) premium for market risk (as the valuation is sensitive to market factors); (c) premium for considering only successful scenario (since the VC method does not consider probability weighted scenarios); and (d) premium for possible dilution in equity (there could be possibility of subsequent rounds of funding before the exit of early-stage investor). Therefore, the preferred discount rate would be much higher than the traditional cost of capital measure that uses only the first two factors. It is not easy to estimate the last two factors. One way to measure the premium for successful scenario is to collect information on start-ups that are successful in raising multiple rounds of funding in first 7-10 years. The difference

[6] https://entrackr.com/2018/01/zomato-valuation-morgan-stanley-2-5-bn/ (accessed on 17 May 2018)
[7] https://tech.economictimes.indiatimes.com/news/startups/softbank-tiger-global-back-grofers-with-rs-400-crore/63341077 (accessed on 17 May 2018)

in the valuation of these start-ups between the first round and the latest round of funding can be explained by increase in earnings and earnings multiple as well as decrease in discount rate (Table 2).

Table 2: Example of Premium for Success (*revenue figs in Rs. Crore)*

Start-up	Vintage	Revenue (2018)	Revenue (2022)	Valuation	P/S	IRR
ABC	2017	1	50	135	10	30%
XYZ	2015	75	250	2500	22	17%

ABC is a pre-revenue company by our definition and XYZ has seen some success. Both the start-ups raised money in 2018 at respective valuations. The IRR is derived from the enterprise value. The difference in IRR (13%) may be attributed as the premium for success of ABC.

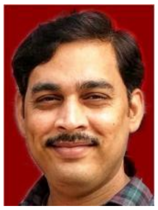
One may not include any premium for possible dilution in ownership in the discount rate and take care of such eventuality separately by way of warrant. The next issue of Artha will discuss this feature in details.

A higher rate of discount also compensates for any unsubstantiated optimism in revenue projections. Typically, any entrepreneur would have emotional bias for revenue projections and she would tend to overestimate future revenue. The early-stage investor will in such a case use a higher discount rate to offset such optimism. The discount rate that is prevalent to value such start-ups varies anywhere between 25% and 40% depending on nature and complexities of the business, patent on product/service, and scalability.

Thus, valuation of pre-revenue companies is an art and involves deep understanding of business models. It also requires one to have sufficient information about the private equity market and the valuations at which early-stage start-ups have recently raised money.

Listing Price Manipulation and Grey Market Trades in Indian IPOs

Sudhakara Reddy



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On 10th July, 2017, the listing day of AU Small Finance Bank surprised the market as the pre-open price discovered for the IPO was Rs. 525 per share versus the issue price of Rs. 358 per share giving a premium of Rs. 167 per share. The small investors who sold their shares in the *Grey Market* were unhappy as they thought that they could not cash on the superlative listing gains given by the IPO. If we closely look at the firm in the Grey Market, the initial Grey Market Price/Premium (GMP) was Rs. 78 over the probable listing price and touched a high of Rs. 135 per share.[8] However, there is no reason for the small investors to worry if they would not have entered the market only to gain listing day returns, they would have been trapped because of the sudden plunge in the price the next day. High Networth Individuals (HNIs) generally avail margin funding and trade in the grey market to make easy profits by bidding in the HNI category of the issue.[9]For example in the case of AU IPO, HNIs portion was oversubscribed 144 times. That is for every one share allocation, HNI has to pay Rs. 51,552 (offer price 358*144). If the HNI avails a finance of 98% at an interest rate of 7% per annum and pays a margin money of Rs. 1032, his net gain would be Rs. 31 per share in about ten days.[10]This implies that to make these easy profits they oversubscribe for more shares get the allocation and sell for a premium.

On the other hand, the operators bought the shares of AU IPO at a premium from the HNIs (and retail investors too) in the grey market (by paying an average price of Rs. 475) and it has been understood that they purchased all the available shares from the market on the listing day as most of the investors look for listing day gains. In the present case, operators mopped up around ten million shares and held them till the weekend. In the meantime, the uninformed investors believed that the shares were very valuable and bid at higher prices. In the case of AU IPO,

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[8] Information retrieved from: https://www.moneycontrol.com/news/business/ipo/operators-manipulating-price-of-latest-ipo-listings-by-cornering-shares-writes-sp-tulsian-2326949.html

[9] According to SEBI, 15% of the IPO shares are reserved for the HNI category

[10] Interest cost at 7% per annum for 6 days is Rs. 59 and the average grey market premium is Rs. 90. The profit is 90 – 59 = Rs. 31

within four days (14th July) the volume traded was about five million shares of which four million were supplied by the operators at an average price of Rs. 675 per share making a cool profits of over 100 crore rupees. The above explains the prevalent price manipulation in the IPOs through the grey market.

The past two years have been massive in terms of IPO listings in India. There are more than 200 firms which have debuted on the Indian bourses during this period and there are many more to follow suit. Most of the companies gave strong returns on the listing day. Market analysts argue that stocks get trapped because of the irrational buying and leave little float for public to trade. The abnormal listing day returns for some of the IPOs (for example, Everonn gave a listing day return of 240% in 2007) resulted in a very active Grey Market for IPOs. The grey market in India is as unregulated as any other grey market (when-issued market) around the world. It is essentially an OTC market where operators execute orders for their clients as well as support the IPO. It acts as a platform for traders to trade in the IPO shares even before the shares are listed on the bourses.[11] The GMP is the premium demanded over and above the possible listing price. The initial GMP is set by merchant banker in consultation with the company promoter and market operators. This is important for the issuers as it shows the demand for the IPO before the issue. The sentiment of the market and pricing of the issue also decides the trends in the grey market.

The following is an analysis of NSE IPOs for the past 6 years from Jan-2012 to Dec-2017. Table 1 shows the descriptive statistics of 356 IPOs where the average underpricing or listing day returns are 22.17%.

Table 1: All Firms

Variable	No. of firms	Mean	Std Dev
Underpricing (%)	356	22.17	45.12
Retail Oversubscription (times)	356	9.74	14.80
HNI/NII Oversubscription (times)	356	31.13	50.13
QIB Oversubscription (times)	356	20.59	33.08
Total Oversubscription (times)	356	18.58	25.90
Deal Size (Rs. Crore)	356	432.53	1257.45
Return 1-week after IPO (%)	356	-1.49	17.00
Return 1-month after IPO (%)	356	-3.77	32.21
Return 1-quarter after IPO (%)	356	-2.65	59.24

Source: Prime Database (author's computations)

[11] More information on the working of Grey Market in India can be read at: https://www.moneycontrol.com/news/business/ipo/decoded-grey-market-in-ipos-and-how-it-influences-listing-day-price-2327567.html

It can be seen from Table 1 that the highest over-subscription is by the HNIs at an average of 31.13 times. Whereas the oversubscription by retail and QIBs are 9.74 and 20.59 times. Even though the first day returns are 22.17% on an average, a week after the IPO, the average returns are -1.49%. Similarly, the returns after a month and after a quarter are more negative. This is how the operators make the profits and the uninformed investors bear the losses as shown in the AU IPO case.

We split the sample into subsamples of large and small IPOs to see whether there is a manipulation only in small IPOs as large IPOs are not easy to manipulate because of their visibility and presence of reputed underwriters.

Table 2: Large Firms			
Variable	No. of firms	Mean	Std Dev
Underpricing (%)	178	18.99	34.45
Retail Oversubscription (times)	178	8.00	11.55
HNI/NII Oversubscription (times)	178	37.02	51.71
QIB Oversubscription (times)	178	30.54	40.91
Total Oversubscription (times)	178	24.08	29.53
Deal Size (Rs. Crore)	178	800.91	1702.27
Return 1-week after IPO (%)	178	-0.03	12.65
Return 1-month after IPO (%)	178	-1.66	23.25
Return 1-quarter after IPO (%)	178	-3.17	40.45
Source: Prime Database (author's computations)			

But, surprisingly, Table 2 shows that the results are almost similar to Table 1. Even the oversubscription by HNIs is slightly higher at 37 times for the large IPOs compared to 31 times for all IPOs.

Table 3: Small Firms			
Variable	No. of firms	Mean	Std Dev
Underpricing (%)	178	25.36	53.63
Retail Oversubscription (times)	178	11.47	17.32
HNI/NII Oversubscription (times)	178	25.25	47.91
QIB Oversubscription (times)	178	10.63	17.95
Total Oversubscription (times)	178	13.12	20.37
Deal Size (Rs. Crore)	178	64.14	25.08
Return 1-week after IPO (%)	178	-2.90	20.29
Return 1-month after IPO (%)	178	-5.82	38.95
Return 1-quarter after IPO (%)	178	-2.14	73.13
Source: Prime Database (author's computations)			

Similarly, in the case of small IPOs, the oversubscription by HNIs is 25.25 times. Interestingly, in this case the average oversubscription by retail and QIBs is almost same and is not the case with the large IPOs.

Table 4: Small IPOs with Reputed Underwriters			
Variable	No. of firms	Mean	Std Dev
Underpricing (%)	32	46.36	61.88
Retail Oversubscription (times)	32	21.10	22.65
HNI/NII Oversubscription (times)	32	54.83	73.66
QIB Oversubscription (times)	32	20.70	20.30
Total Oversubscription (times)	32	26.77	25.36
Deal Size (Rs. Crore)	32	77.49	24.22
Return 1-week after IPO (%)	32	4.30	14.30
Return 1-month after IPO (%)	32	5.72	26.49
Return 1-quarter after IPO (%)	32	10.83	53.87
Source: Prime Database (author's computations)			

Table 5: Small IPOs with Unreputed Underwriters			
Variable	No. of firms	Mean	Std Dev
Underpricing (%)	146	20.75	50.73
Retail Oversubscription (times)	146	9.36	15.21
HNI/NII Oversubscription (times)	146	18.77	37.50
QIB Oversubscription (times)	146	8.42	16.67
Total Oversubscription (times)	146	10.13	17.85
Deal Size (Rs. Crore)	146	61.22	24.38
Return 1-week after IPO (%)	146	-4.39	21.05
Return 1-month after IPO (%)	146	-8.21	40.72
Return 1-quarter after IPO (%)	146	-4.83	76.39
Source: Prime Database (author's computations)			

We further divide the small IPOs into two subsamples of IPOs with reputed underwriters and IPOs with unreputed underwriters and examine whether there is any difference in the statistics. The total number of small IPOs with reputed underwriters is 32 out of 178 and the remaining small IPOs are managed by unreputed underwriters. The results are strikingly different. Table 4 shows the descriptive statistics of small IPOs with reputed underwriters and Table 5 that of small IPOs with unreputed underwriters. It can be seen that even though the listing day returns are very high for IPOs with reputed underwriters, the returns after the IPO are also positive with the quarter after the IPO returns as high as 10.83%. But, that is not the case with small IPOs with unreputed underwriters as the returns after the IPO are significantly lower compared to Table 4 as well as statistics of overall IPOs. From the above analysis it can be seen that the maximum manipulation happens with small IPOs managed by unreputed underwriters. However, direct evidence of this manipulation is not possible with the data that is available with us.

The entire practice of manipulation is similar to a casino and the big operators are not understanding that they are imprudently killing the golden goose and will not get the golden eggs in the long run.

It is high time that SEBI takes serious note of these manipulations and devise appropriate measures in the interest of the smooth functioning of the capital markets and also the economy as a whole. Any further delay may result in retail investors opting out of the capital markets. Very recently in November 2017, a committee formed by SEBI has proposed a 10% circuit filters on the first two days of the listing which is not seen positively by a section of the market as volatility on the listing day is essential for the proper price discovery. This issue of manipulation should be dealt with more effectively without any hindrance to the normal trading process.

ALUMNI CORNER

With Ind AS accounting standards, India moves towards the fair value regime

Balachandran R

Balachandran R is an alumnus of IIM Calcutta (1987-89) with extensive experience in corporate banking, investment banking and product management.

A global set of accounting standards was pioneered by the International Accounting Standards Committee, which was set up in 1973. The standards were called IAS Standards. Its successor the International Accounting Standards Board (IASB) developed the International Financial Reporting Standards, the IFRS, used by publicly accountable companies. About 87% of jurisdictions in the world require the use of IFRS standards. The IASB was established in 2001 and has stakeholders from around the world.

IFRS seeks to bring transparency by enhancing the international comparability and quality of financial information, enabling investors and other market participants to make informed economic decisions.

The Financial Accounting Standards Board (FASB) in the United States was established in 1973 to formulate financial accounting and reporting standards for public and private companies and not-for-profit organizations.

While the IFRS is currently not applicable in the United States, the FASB of the US is working with the IASB on a convergence project with IFRS. Considerable progress has been achieved in this direction.

INDIAN ACCOUNTING STANDARDS (Ind AS)

For the Indian jurisdiction, the Ministry of Company Affairs has notified the Indian Accounting Standards (Ind AS) with the date of transition as 1st April, 2015.

In Phase I, Ind As is applicable from 1 April 2016 to listed and unlisted companies whose net worth is greater or equal to Rs 500 crores. In Phase 2, it is applicable from 1 April 2017 to all listed companies; applicable to unlisted

companies whose net worth is equal to or greater than Rs 250 crores. Ind AS applicability has been deferred for insurance companies, banking companies and nonbanking finance companies.
The Indian Accounting Standards are based on the IFRS, but with certain differences. India has chosen the path of convergence with IFRS rather than outright adoption.

STATEMENT OF PROFIT AND LOSS

A significant change in Ind AS as compared to the previous GAAP is the presentation of the Statement of Profit and Loss. Profit and loss and Other Comprehensive Income are presented in separate sections within a single statement of profit and loss.

OCI conceptually aims to capture those components of profits that are outside a company's core operations or volatile in nature. OCI is therefore excluded from calculation of Earnings Per Share, a key measure from a shareholder perspective.

INVENTORIES

Inventories are initially recognised at the lower of cost and net realisable value (NRV).

Ind AS requires the cost for items that are not interchangeable or that have been segregated for specific contracts to be determined on an individual-item basis. The cost of other inventory items used is assigned by using either the first-in, first-out (FIFO) or weighted average cost formula. Last-in, first-out (LIFO) is not permitted.

The FASB permits LIFO method on the US, but the Internal Revenue Services, the equivalent of the Indian Income Tax Department, requires that companies using LIFO inventory costing for tax purposes also use it for financial reporting.

Indian companies have generally adopted the weighted average or FIFO method.

PROPERTY, PLANT AND EQUIPMENT

PPE is measured initially at cost. Subsequently, they are carried at historical cost less accumulated depreciation and any accumulated impairment losses (the
cost model), or at a revalued amount less any accumulated depreciation and subsequent accumulated impairment losses (the revaluation model).

The depreciable amount of PPE (the gross carrying value less the estimated residual value) is depreciated on a systematic basis over its useful life. The straight line method is commonly used in the Ind AS financial statements of Indian corporates, though instances of written down value method of depreciation has also been observed.

There is no significant impact on financial statements on account of the new Ind AS standards as compared to the previous Indian GAAP for non-financial assets like PPE and inventory**.**

FINANCIAL INSTRUMENTS

Financial instruments include a wide range of assets and liabilities, such as trade debtors, trade creditors, loans, finance lease receivables and derivatives. The erstwhile IAS 39, the current IFRS 9 and Ind AS 109 deal with financial instruments.

Classification, recognition and measurement principles for financial instruments is one of the most significant changes in Ind AS as compared to the previous Indian GAAP.

Financial assets and financial liabilities are initially measured at fair value, which is usually the transaction price. Subsequently, financial instruments are measured according to the category in which they are classified.

DEBT INSTRUMENTS

A financial asset that meets the following two conditions is measured at **amortised cost:**

• Business model test: the objective of the Company's business model is to hold the financial asset to collect the contractual cash flows.
• Cash flow characteristic test: the contractual term of the financial asset give rise on specified dates to cash flows that are solely payments of principal and interest (SPPI) on the principal amount outstanding.
Instruments with contractual cash flows that are SPPI on the principal amount outstanding are consistent with a basic lending arrangement.

A financial asset that meets the following two conditions is measured at **fair value through other comprehensive income (FVOCI):**

• Business model test: the financial asset is held within a business model whose objective is achieved by both collecting cash flows and selling financial assets.

• Cash flow characteristic test: the contractual term of the financial asset gives rise on specified dates to cash flows that are SPPI on the principal amount outstanding.

Movements in the carrying amount are recorded through OCI, except for the recognition of impairment gains or losses, interest revenue as well as foreign exchange gains and losses which are recognised in profit and loss.

All other financial assets are measured at fair value through **profit or loss (FVTPL).** Financial assets included within the FVPL category need to be measured at fair value with all changes recorded through profit or loss.

Analyzing the financial statements of large Indian corporates reveals that debt mutual funds are the favoured choice of investment. The debt fund industry with a size of around USD 170 billion owes its corpus largely to corporate treasuries. Investments in debt based mutual funds are usually measured at fair value through profit and loss as there is no contractual commitment by asset management companies to pay a fixed return, though some such investments have been measured at fair value through OCI.

Equity instruments

Investments in equity instruments are always measured at fair value. Equity instruments that are held for trading are classified as FVPL. For other equities, management has the ability to make an irrevocable election on initial recognition, on an instrument-by-instrument basis, to present changes in fair value in OCI rather than profit or loss.

Derivatives

Derivatives are measured at fair value. All fair value gains and losses are recognised in profit or loss except where the derivatives qualify as hedging instruments in cash flow hedges or net investment hedges.

Impairment

Ind AS specifies a three-stage model based on expected credit losses for impairment depending on changes in credit quality since initial recognition.

IMPACT ON SHIFT FROM PREVIOUS GAAP TO IND AS

The bulk of assets and liabilities are carried at amortized cost in the Ind As statements for FY 2016-17. This does not have a significant impact compared to the erstwhile gap. The major exceptions are financial assets comprising of debt mutual funds, certificates of deposit and bonds/debentures which are classified as FVTPL or FVOCI.

Disclosures of reconciliations from Indian GAAP to Ind AS are required. Analysis of the financial statements of some of the largest listed companies in terms of market capitalization, reveals some interesting trends based on these disclosures.

The profit after tax/total comprehensive income for an automobile major increased by 17% primarily because of debt mutual funds measured at fair value as per Ind AS, against cost or lower of cost and market value, in the previous GAAP statement for FY 2015-16. In the case of a refining/petrochemical conglomerate there was a 7% increase in net profit as per Ind AS. In the case of two of the largest information technology companies, there was a negligible change in total comprehensive income as per Ind AS compared to previous GAAP. For a large FMCG company, there was a 6% drop in total comprehensive income and for another it was negligible.

With the comparative statements showing a small difference in many cases and positive variation in some cases which goes against conservatism, and a muted change on an average, one wonders if the gargantuan exercise of adopting the new standards helped the consumers of the financial statements in any significant way. Perhaps, in volatile years, the statements will reveal the stark distinctions between profit and loss and OCI. But it would be difficult to assess, how the figures would have compared with the financial statements under the previous Indian GAAP. With Ind AS not aligned 100% with IFRS, international comparability too is not feasible.

NEW ACCOUNTING RULE IN THE US

The entities under US jurisdiction have some interesting times ahead of them. A new accounting standard applicable from January 2018, requires unrealized gains and losses in marketable and non-marketable equity securities, to be included in net income. Warren Buffet, the Chairman of Berkshire Hathaway in his annual letter to shareholders laments that this will produce some “truly wild and capricious swings” in the company’s bottom line. Realized gains were required to be reported in net income before the new rule, and even that was considered to distort the income statement. The impact extends beyond investment companies. Google too has issued a statement that the new rule will increase volatility in Other Income and Expense in the Income Statement.

As the accounting world moves towards a "truly" fair value world, financial statements may make less sense to shareholders, creditors and other stakeholders, in the traditional way. Perhaps, financial statements should henceforth be viewed through the prism of change in net asset value based on fair value, rather than the current focus on profit and loss/net income.

VOICE OF AMERICA

Great Expectations

Ayan Bhattacharya

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Many analysts have marked the record sale of Flipkart's stake to Walmart this month as a turning point in India's startup ecosystem. The thinking behind the optimism is simple: as developed markets age and slow, big players can ignore India only at their own peril. After all, no serious venture would want to miss being part of the India story, especially as the Chinese miracle plateaus off! Less than three years back, however, it was a completely different tale. Many international investors were then busy marking down their India portfolios as a series of startups—most notably Housing.com—began imploding under the pressure of scaling up. What changed between then and now? One could come up with a variety of reasons, but underlying all of them would be a single idea: change in expectations.

Unlike any other field, finance, almost entirely, is fueled by expectations. Markets—whether formal ones like the financial exchange, or informal ones like the neighborhood kirana store—name a price almost always before the fact, in expectation. But what exactly is this expectation?

1. How Do We Expect?

For a field so dependent on the notion of expectation, you would presume finance to have a clearly articulated, experimentally verifiable definition of the notion. That, sadly, is not the case. In fact, the deeper you dig, the more slippery it becomes. Financial accountants will tell you confidently that expectation is all about analyst forecasts, but push them about where forward looking parameters in analyst models come from, and the consensus will disappear. Financial statisticians, on the other hand, will give you a fancy formula for expectation: just multiply the probability of a scenario by its outcome, across all scenarios. But push statisticians about where exactly these probabilities come from, and they will go silent. Expectation, at its core, seems to be closely linked to our human ability to learn, and the budding field of cognitive neuroscience is increasingly making clear to researchers the huge gaps in our current understanding of our own brain's ability to learn and form expectations. Yet the business of expectations has always been at the heart of finance.

The basic "atoms" of finance are prices, and the price of any asset, whether physical or financial, is the value that a buyer hopes to derive from its possession in the future. This value is all about expectations, because the future is yet to unfold when the transaction is sealed. Different people may *expect* to derive different value from possession, or they may *expect* the future to unfold differently—thus they bargain and trade. So how does finance come up with explanations for prices despite the many gaps in our current understanding of expectation formation? Well, as we'll see below, by a shrewd sleight of hand!

2. Expecting Without Expectations

Many early economists struggled with the notion of expectations. John Maynard Keynes, arguably the most influential of last century's economists, spent many years thinking about the origin of probability and expectations before embarking on a full-time career in economics [1], and many of his influential macroeconomic theories demonstrate a deep appreciation of human expectations. Yet, he never put forward a rigorous formulation. It took many years and many false starts before the field hit upon two novel ways to handle expectations.

The first was the concept of rational expectations. In a pioneering paper in 1961, John Muth, then at Carnegie Mellon University, proposed the idea that rational economic agents' prognosis about the future should be consistent with the economic models used to predict the future [2]. The underlying principle was one of consistency. Sitting today if an agent posited a model of the future that included the agent himself, yet did not behave according to his own model's prediction when the future actually unfolded, he would be irrational! Such irrational agents would surely not be interesting economic agents, it was believed, since they would fall a prey to Darwinian survival. A similar idea animated Harsanyi's extension of game theoretic equilibrium to incomplete games [3]. Thus economic agents' expectations of the future was encapsulated in the models they built today, and at the same time, the models they built today had to be accurate descriptions of the future, since all agents were rational. In effect, economists had managed to replace the neurobiological mechanism of expectation formation with the logical apparatus of consistency! Many of the widely influential theories of finance that explain asset prices, starting with the Capital Asset Pricing Model, rely on this logical apparatus.

The second was the technique of no-arbitrage, or no-free lunch. No-arbitrage simply meant that there could be no free profit opportunities in the price system, because if there were, everyone would go after them, and they would evaporate instantaneously. No-arbitrage started with a bunch of given expectations (or prices) and was agnostic about where these baseline expectations came from. The power of this theory was in using the technique of no-arbitrage to derive other expectations in the economy once the baseline expectations were assumed as given.

Once again, the underlying principle driving the technique was consistency. The baseline expectations could be arbitrary in principle, but all other expectations in the economy had to follow consistently from them. Once more, the neurobiological mechanism had been cleverly avoided using the logical apparatus. The Black-Scholes-Merton option pricing and many other theories of finance exploited this technique to great effect.

Dissatisfied with these techniques derived from logic, some finance researchers began dabbling in ideas from cognitive psychology in the hope of understanding human behavior better. This led to the birth of behavioral finance. While the new approach provided many new insights, it still depended on a notion of consistent expectations for aggregate predictions. The problem really was that researchers did not (and still do not) fully understand the internal algorithms of the brain. Cognitive psychology largely depended on outcomes of experiments to infer how people think. While this was an improvement for finance, the black box of actual expectation formation still remained out of bounds. At the same time, the apparatus already developed by the logic based techniques were mathematically rigorous, reasonably simple to use, and provided useful predictions. Over time, with minor tweaks, the behavioral methods were co-opted into the logical framework.

3. Can Logic Fail?

The big question, then, for researchers and practitioners is: when and how—if ever—does the consistency based logic underlying expectations fail? Can financial modelers know in advance, before events really move off the grid? In other words, sitting through the Housing.com fiasco in 2015, could one have rationally expected the bounce-back in India's startup scene? The question is also important for regulators, since regulatory approval, too, is based on anticipation of future impact on the competitive landscape. So for those reading between the lines, most of the briefs to the US district judge deciding the $85 billion merger between AT&T and Time Warner in the last few months have been really about competing visions and expectations of the future [4].

Researchers realize that understanding the departure of expectations from predictions is an important question, and it is high up on their "to-comprehend" list. Yet the honest answer at the current moment is that we do not know how it happens. Two paths seem to be emerging in the literature, however. One, pioneered by the late Stephen Ross, is the Recovery theorem approach [5]. Briefly, the idea is to recover accurate expectations from empirically available market prices, rather than rigidly impose theoretical no-arbitrage conditions. The second, inspired by the artificial intelligence literature in computer science, is to approximate the process of expectation formation through variants of machine learning algorithms [6]. Both are still nascent approaches, and it is anybody's guess as to which path will be successful. Real life expectations, after all, are way more complicated than Dickens' fictional Great Expectations!

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