LEARNING FROM TRADING WITH AMBIGUOUS INFORMATION

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Abstract - In this paper we study long-term learning process under the conditions of ambiguous information. We study a unique empirical setting in which pieces of the ambiguous information about the value of corporate bonds are sequentially provided to institutional investors. We use parametric and non-parametric models to show that exits a continual convergence process that it is non-linear. We show that the learning process is strict and that the convergence is towards an unbiased point that represents the set of prices which are dictated by the available information. The theoretical and experimental literature on learning processes is rich, but there are only a handful of empirical studies. We contribute direct empirical evidence that supports important theoretical and experimental predictions.

Keywords - Ambiguous Information, Learning Process, Trade, BondsJEL Code: G12, G23, G24

I. INTRODUCTION

This paper examines the long-term learning process of institutional investors. The information they learn is about external valuation of other bonds that are not traded. The investors learn to evaluate the impact of the changes in the price of the non-traded bonds on the value of traded bonds. Learning processes typically take place under conditions of ambiguous information: The investor cannot establish not only the valuation distribution moments (expected return, volatility) but also what type of distribution it is. We study a unique empirical setting in which pieces of ambiguous information about the value of corporate bonds are sequentially provided to institutional investors. We use parametric and non-parametric models to show that exist a non-linear convergence process. Our motivation is to better the understanding of the dynamics of the discovery process. In particular, we want to understand the impact of gradually revealing ambiguous information on prices, variance, and volumes of trade. Furthermore, we examine the underlying principles that operate during price discovery and information aggregation processes. First, how do asset prices react to ambiguous information? Second, once the ambiguity is clarified, does the learning process take a different and specific shape? What are the factors behind the discovery process?

II. LITERATURE REVIEW

The Efficient Market Hypothesis (EMH) is based on the assumption that market prices represent all available information. Both the classic and the modern definitions of EMH are complete only if the information is embedded in the prices and volatilities instantaneously. Much of the theoretical and experimental literature focus on the nature of the price discovery process (i.e. learning curve) when the price convergence process is extended.For the most part, the principles that were developed in theory have proven to be significant tools in predicting and explaining experimental observations. Information arrival models, in particular, sequential information arrival models, have been presented since Copeland's (1976) seminal work. Copeland shows that with sequential information arrival, the price change between the initial and final equilibria is known with certainty, just as in a world with simultaneous information arrival. However, the path of adjustment, which Copeland (1976) refers to as the learning curve or the learning process, can take one of the several distinct shapes. The specific parameters of the process relate to the characteristics of the market. Jun and Vives (2004) and Vives (1993, 2008) argue that learning the unknown parameter does not yield the same results as convergence to a bounded equilibrium with accurate expectations. Vives (1993) models the learning rapidity from market prices and finds a slow convergence to the rational expectation equilibrium: approximately at the rate of $1/\sqrt[3]{n}$where n is the number of periods of market interaction. This is true only when the average precision of private information in the market is finite.

In another work, Vives (2008) distinguishes between learning within equilibrium and learning about equilibrium. In other words, he differentiates between a learning process within rational expectations and a learning process about rational expectations. The learning process can be Bayesian or of another type, as it will be shown here. When learning in equilibrium, agents make the most efficient use of their information, and therefore, the procedure must be Bayesian. Leipold et al. (2008) suggest a framework for asset pricing implications of learning under ambiguity aversion. Learning under ambiguity aversion implies an equilibrium discount for ambiguity, if the Elasticity of Intertemporal Substitution (EIS) is above one. In this case, ambiguity aversion increases both equity premia and volatilities. Barner et al. (2013) present an experimental study of adjustment process (AP). Their experiment is designed such that information gets into the market and is captured by a type of path dependence that can take several forms; this is called

the fundamental coordination principle of information transfer. The early trades tend to be initiated by insiders who limit orders. The emergence of bubble mirages or any non-smooth paths are coincident with failures and circumstances that prevent operation of the fundamental principle. Several works document SIAH effects in stock markets. Darrat et al. (2003) use intraday data to measure return volatility by exponential GARCH. Illeditsch (2009, 2010) studies the effects of aversion to risk and ambiguity on the value of the market portfolio when investors receive public information which they find difficult to link with fundamentals; they are inclined to treat it asambiguous. Illeditsch (2009) shows that small changes in public information can produce large changes in the stock price and that systemic negative news may lead to higher valuations of the stock market. An aversion to ambiguity can explain excess volatility and kurtosis of returns. Illeditsch's (2010) model predicts that when news is surprising, some investors may not react to price changes, although there are no transaction costs or other market frictions. Moreover, Illeditsch (2010) shows that under sufficient ambiguity, small shocks to supply or demand may lead to drastic changes in prices and hence to excess volatility. Time and trading impose a closed set of plausible price behaviors. Copeland (1976) as well as Forsythe et al. (1982, 1984) and Friedman et al. (1983, 1984) indicate that markets are capable of guiding a converging price discovery process. However, speculations and other features of agent's choices can produce bubbles and other forms of unexpected behavior (Rockenbach 2004), rendering the reverse sigmoid (or any other strictly converging learning function) to be anything but a trivial and inconsequential solution. Bubbles and other forms of higher volatility and superfluous volume, which appear to be at odds with a punctilious development of the market, are offset by agents' heterogeneity (Kluger and Wyatt 2004). information arrival on the market within a single period. They show that markets are sensitive to the setting and the dimensions of information arrival butfind mixed results regarding the capacity of markets to fully reveal the information, as predicted by Copeland (1976). Camerer (1999) demonstrates the existence of information traps that can occur as a result of coordination and constraints that results from the diverse availability in time to the various agents. In an empirical work on ambiguity, Melvin and Eaves (2005) examine the Tokyo Grain Exchange's futures contracts by putting into their service sequences of electronic auctions. The lengths of auctions are endogenous; thus, the TGE offers an obvious measure of the length of time that it takes to prices to converge into equilibrium. Melvin and Eaves (2005) find that the convergencerate is positively affected by informed trading among exchange locals and off-exchange customers. Informed trades by customers are more important than those that are informed by exchange locals when little public information is available.

III. SETTING

In 2004, the savings and pensions commissioner at the Treasury issued a Request for Bid (RFB) for the implementation of a practical fair value (FV) model. This model was to embody the valuation of non-tradable assets, especially non-listed bonds, which comprise more than 70% of the non-tradable assets in the portfolios of institutional investors. In August 2004, a special purpose company named RBT (www.rbt.co.il, hereinafter "RBT"), sponsored by Global S&P, won the bid. RBT submitted the Nelson-Siegel's (1987) model, mainly due to its robustness for small datasets. RBT started to test the model in early October 2004 using sample portfolios. After facing some technical difficulties it was launched on April 2, 2005.Over the years, most of the debt in Israel was issued fully-linked to the Consumer Price Index (CPI). By 2005, 65% of the sovereign debt and 92% of the corporate debt was CPI-linked; by 2012, the figures dropped to 49% and 84%, respectively. We limit most of our analysis to the CPI-linked bonds. The FV model which was introduced to the market on April 2005 is based on the Nelson-Siegel's (1987) model with various modifications. By using the weekly bond prices traded on the TASE, the outputs are used to compute the appropriate yield for each rating. The weekly valuation was published every Thursday between 17:00, when the daily exchange trading ends and 18:00. There is no trade on Fridays. The market is not exposed to the structuring of the information, including what days are included in the sample and their weights. Traders can estimate the expected yield given their Bayesian predictions.

Trade	Sunday 9:10 – Thursday 17:00	Thursday, 17:00-18:00	Thursday-Friday	Sunday 9:10 – Thursday 17:00	Thursday, 17:00-18:00	Thursday-Friday
RBT	Information from the market. Filtering methods are exercised	matrices are published		Information from the market. The same filtering methods are exercised	matrices are published	
Market	Trade. Review prices		Matrices are used to compute prices of illiquid assets	Trade. Review prices + Bayesian updating; conditioned on previous week yields		Matrices are used to compute prices of illiquid assets+ review of tracking error
	Week t			Week t+1		

IV. DATA

Due to the scarcity of the data, we analyze only AA+ to A- ratings. The market lacks a sufficient supply of AAA-rated bonds, as there are only three issuers rated AAA. At the other end of the rating ranking, there was no listing of BBB or below. To achieve more robust portfolios, we group the non-traded bonds into clusters:

1. RF bonds 2. AA Bonds (AA+, AA, AA-) 3. A bonds (A+, A, A-) 4. BB.

Twenty of the high volume/high trade frequency unrated bonds were rated by S&P-Israel for the sole purpose of structuring the BBB+ and BBB vectors. This is done without a disclosure regarding the fact that the rating process ever took place. The S&P uses public information only, so the rating is not below the par of full ratings. The rating is per category and not per notch. The number of bonds in each cluster varies over the model period. For each rating class, there were 6 to 11 bonds at the beginning of the sample period (December 2004) and 10 to 20 bonds at the end of the sample period. For all corporate rating classes, the number of bonds increased over time. The risk-free class included 19 bonds at the beginning of the sample period but decreased to 16 at the end of period. The BBB internal class is structured using 12 to 18 bonds.

The structure of each yield is technically bounded by its senior: The location of the hump (δ) is fixed by the location of the hump of the RF curve. The intersection of a senior curve by a subordinated curve is ruled out by limiting $(\alpha;\beta)$ such that:

$$\begin{bmatrix} \beta_{AAA} \geq \beta_{RF} \\ (\alpha+\beta)_{AAA} \geq (\alpha+\beta)_{RF} \end{bmatrix}$$

The market is not knowledgeable as to what information is included and excluded from the FVmodel.. Another important and unknown piece of information is the lag: the information is published at the end of the trading week (Thursdays at 18:00); however, given the need to incorporate index information and to provide the Treasury with the information earlier than 18:00, the investors do not know that Thursday's information is omitted from the model. These uncertainties create an endogenous surprise effect. Even if all traders accepted RBT's prices as unique and correct, there would always be an embedded error factor. The expected surprise effect and the variance are computed as

$$\bar{\varepsilon}_i = fv_i - p_i^{wed.} \quad (2.3)$$

$$Var_i = (fv_i - p_i^{wed.})^2 \quad (2.4)$$

We sample the data over a period of 98 weeks, the point of departure of which is the first week of December 2004, four months before the introduction of the model. These are the first available data points. The end-point of the measurement is October 26, 2006. In September 2006, some of the restrictions behind the corporate vectors of the model were watered down, allowing for a better fit and thus changing the model. As this change occurs deep into the plateau period of the learning curve, it has no effect. We find that the difference in pricing between the old and new methodologies is insignificant. There is no significant additional learning. Table 4 shows the changes in the smoothness of the convergence curve. We test the two samples of 40 observations by the Kolmogorov–Smirnov (K-S) test. We use the K-S, because it allows for comparison between the functions of the empirical distribution of the two samples without any restrictions on the cumulative distribution function CDF. The null distribution of this statistic is calculated under the null hypothesis that the samples are drawn from the same distribution (in the two-sample case). The NR is sufficiently close to the 90% threshold. Thus, we terminate the sample period at September 2006.

V. RESULTS

VOL: Volume, computed weekly per cluster
INT: Basic interest rate, measured over the short-term Treasury curve
SPR: The relevant corporate spread above the sovereign curve, computed weekly per cluster
ECPI: Expected inflation, calculated from the sovereign bonds yields
WAR: Dummy variable ascribed to the five-week period of July 12, 2006 to August 15,

The control variables are far from significant, except the WAR dummy. Our parametric model is not based on ordinary financial variables but rather on information accessibility. Using RBT's private database, we calculate the number of users logged into the system at any given week. Each user receives a unique I.D., so the number of identified log-ins represents the number of users who were exposed to the information directly. A repeated entry from the same user is counted twice. We suggest that the number of users is a good proxy for the spread of information. If a user logs in more than once or twice, then she might be using the database for more than downloading matrices. However, the log-ins figures suffer from under-representation, as the entry codes likely circulated between authorized and external users. There is no available information on how many users logged in during the pre-launch period of the system before April 1, 2005. The system was tested as a Beta version during March 2005, but no log records are available. The login statistics are available in two forms:

QLOG: The number of qualified investors having access to the system (the number of institutions that de-factoreceive the information); and

LOG: The total number of weekly logins, amounting to the number of logins (unique I.D.) per qualified investor.

LOG and QLOG are not highly correlated. Some institutional investors use the data only for its original purpose, while others (perhaps institutional investors who also manage mutual funds and/or brokerage activity) use the data for benchmarking the trade.

We use this data as proxy for data reliability (DR), such that $DR = {}^{1}/_{\theta}$. Although users were able to log in as many times as desired, and each action was captured separately, we assume that most log-ins aimed to retrieve new information. We define the following regressions. Equation 4.4 computes the variance against the log-ins; equation 4.5 computes the average error against the log-ins

$$Var_i = \alpha + \beta_1 LOG^3 + \beta_2 LOG^2 + \beta_3 LOG + \varepsilon \quad (4.4)$$

$$avg_i = \alpha + \beta_1 LOG^3 + \beta_2 LOG^2 + \beta_3 LOG + \varepsilon \quad (4.5)$$

Panels A and B of Table 4 show the results for the variance changes over time for the AA and A clusters, respectively, regressed against polynomial login. Here, R^2 for both linear and third-order polynomials are significant, reflecting the significant reduction in pricing deviations. For both regressions, the promulgation of information is consistent with the non-linear path suggested by Copeland and Friedman (1987). The power of the polynomial third-order model is significantly higher than the power of a linear model or a second-order polynomial model. For robustness, we check the behavior of models with orders that are higher than three. It is not significantly different than a third-order polynomial model.

DISCUSSION

We contribute to the existing literature by providing direct empirical evidence on the shape and rate of the learning process. Although a considerable number of investors obtain information about which they agree about ex-post. Only a handful of investors can independently estimate the data correctly. Thus, we observe a gradual and not an instantaneous process determined by experience carryover and cessation of learning. These forces are not mutually exclusive (Teplitz 1991); there may be several plausible sigmoid-shaped functions that provide a good fit. Regardless of the chosen function, the empirical results suggest that the incorporation of information and acting upon it is instantaneous ifits value is common knowledge—and if investors act with rational expectations. If investors cannot valuate information ex-ante, then the process of absorbing the information is significantly long. When the number of the informed investors is about 30, a significant convergence path has not yet commenced. The second phase is where most of the improvement in pricing quality is achieved. During this phase, most pricing errors are reduced. The final phase represents the market limit or saturation. Although some additional re-pricing continues, it is at a much lower rate, to such a degree that it becomes asymptotic to the expected surprise effect. We demonstrate that this classic learning process is robust with respect to the level of the fittingness of the information, as long as there is new information. We demonstrate the null hypothesis on two extreme states: when there is nothing new to learn from the additional information and when the information remains private.

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Table 1 Comparative Statistics of the "A" Cluster

rate_nomeric=A+

Variable	N	Mean	Std Dev	Minimum	Maximum
Volume	48	1775775.08	2218244.19	3.80	9217820.80
Yield	48	3.57	1.45	0.96	7.14
Yield_PV	48	3.69	1.04	1.50	5.40
Yield_PV_Yield	48	0.12	0.94	-5.18	1.28
Price	48	117.27	8.29	98.93	150.27
PV	48	116.88	7.21	98.87	148.87
Delta__	48	0.30	2.50	-7.95	4.65
Duration	48	4.33	2.40	1.03	9.83
Duration_PV	48	4.33	2.41	1.03	9.92
Time_to_Maturity	48	2612.27	1368.20	376.00	5854.00
NON_RF_Yield	0	.	.	.	.

Table 1 illustrates the descriptive statistics of the "A" cluster vector, over the sample period. Volumeis the average daily trade; Yield is the average portfolio yield; Yield PV is the average yield computed by the Nelson-Siegel model; Yield_PvYieldis the difference between Yield and Yield PV ;Price is the market price of the "A" cluster portfolio, PV is the value of the "A" portfolio computed by the model; Delta gives the difference between Price and PV; Duration is the Portfolio's average duration; and Time To Maturity is the portfolio's weighted average of time to maturity.

Table 2: Surprise effect and variance over the sample period

	19-Dec-04	23-Jan-05	20-Feb-05	27-Mar-05	24-Apr-05	25-May-05	19-Jun-05	24-Jul-05	21-Aug-05	25-Sep-05
AVG_AA	0.282	-0.268	0.197	-0.045	0.047	-0.197	0.127	-0.046	-0.058	0.093
STD_AA	1.31	0.958	1.656	1.234	1.211	1.371	1.082	0.679	0.619	0.747
AVG_A	0.354	0.235	0.311	0.019	-0.09	-0.106	0.283	0.224	0.111	0.086
STD_A	2.77	2.75	2.55	2.993	3.051	3.715	1.974	1.617	1.393	1.687

	23-Oct-05	20-Nov-05	25-Dec-05	22-Jan-06	19-Feb-06	19-Mar-06	26-Mar-06	23-Apr-06	21-May-06	25-Jun-06	23-Jul-06	20-Aug-06
AVG_AA	0.031	0.083	-0.022	0.037	0.037	0.031	0.04	-0.054	-0.023	-0.046	0.063	0.053
STD_AA	0.925	0.87	0.673	0.607	0.571	0.599	0.518	0.668	0.56	0.677	0.852	0.783
AVG_A	0.147	0.115	0.099	0.066	0.099	0.109	-0.091	0.169	-0.099	0.088	-0.119	0.118
STD_A	0.621	1.131	0.879	1.012	1.431	1.547	1.09	1.768	1.077	0.912	1.141	0.83

Table2 illustrates monthly samples of the main results: Average (AVG) and standard deviation (STD) of the "surprise effect" for the "AA" and "A" class rating clusters. The 1st data point is on December 19th, 2004 and our sample ends on September 1st 2006. The results are presented in normalized points. 1.00 means 100 basis points.

Table 3: Reaction to changes in model parameters

Variable	Standard deviation: until Sep 2006 (n=52)	Standard deviation: after Sep 2006 (n=52)	K-S test P values
AA	0.601	0.594	0.252
A	1.094	1.021	0.341
RF	0.411	0.430	0.442
NR	3.112	2.565	0.107

Table 3 shows the changes in the smoothness of the convergence curve. We test the two samples of 52 observations by the Kolmogorov–Smirnov (K-S) test. We use the K-S because it allows a comparison between the functions of the empirical distribution of the two samples without any restrictions on the CDF. The null distribution of this statistic is calculated under the null hypothesis, according to which the samples are drawn from the same distribution (in the two-sample case). The NR is sufficiently close to the 90% threshold.

Table 4 Panel A: AA cluster bonds. Parametric Model (LOG)

Variable	Coefficient "AA" Cluster	t-Statistic AA" Cluster	Prob. AA" Cluster	Coefficient "A" Cluster	t-Statistic	Prob.
Intercept	1.165118	12.509	0.0000	2.674053	8.325207	0.0000
LOGIN ***	0.0341	3.567	0.001	0.01679	4.012	0.0012
$LOGIN^2$***	-0.0012	-4.153	0.0001	-0.00375	-3.990980	0.0001
$LOGIN^3$***	0.00208	3.791	0.0003	0.00738	3.894531	0.0002
WAR*	-0.0451	1.856	0.028	-0.0251	1.676	0.056
R-squared	0.1999			0.1631		
Adjusted R-squared	0.1767			0.1420		

Table 4 shows the effect of weekly information presentation on the Variance measured over $Var = (FV - \sum P_i)^2$ using the parametric regression $Var_i = \alpha + \beta_1 LOG^3 + \beta_2 LOG^2 + \beta_3 LOG + \varepsilon$ on AA and A clusters rated bonds. WAR is the dummy variable for the weeks of the 2nd Lebanon war (July-Aug 2006) i stands for the specific cluster. *, **, and *** represent significance at the 10%, 5%, and 1% levels respectively.

Table 4 Panel B: AA and A cluster Bonds Parametric Model ((QLOG)

Variable	Coefficient "AA" Cluster	t-Statistic AA" Cluster	Prob. AA" Cluster	Coefficient "A" Cluster	t-Statistic	Prob.
Intercept	5.5618	8.901	0.0000	8.6763	5.5207	0.0000
LOGIN ***	1.421	3.457	0.0002	0.0679	3.567	0.003
$LOGIN^2$***	-0.0132	-3.443	0.0002	-0.0403	-3.650	0.0002
$LOGIN^3$***	0.0318	2.731	0.003	0.0801	3.561	0.0002
WAR	-0.0734	10455	0.343	-0.0l776	0.899	04533
R-squared	0.1766			0.1312		
Adjusted R-squared	0.1402			0.1138		

Table 4B shows the effect of weekly information presentation on the Variance measured over $Var = (FV - \sum P_i)^2$ using the parametric regression $Var_i = \alpha + \beta_1 QLOG^3 + \beta_2 QLOG^2 + \beta_3 QLOG + \varepsilon$ on AA and A rated clusters.). WAR is the dummy variable for the weeks of thewar (July-Aug 2006. *, **, and *** represent significance at the 10%, 5%, and 1% levels respectively.

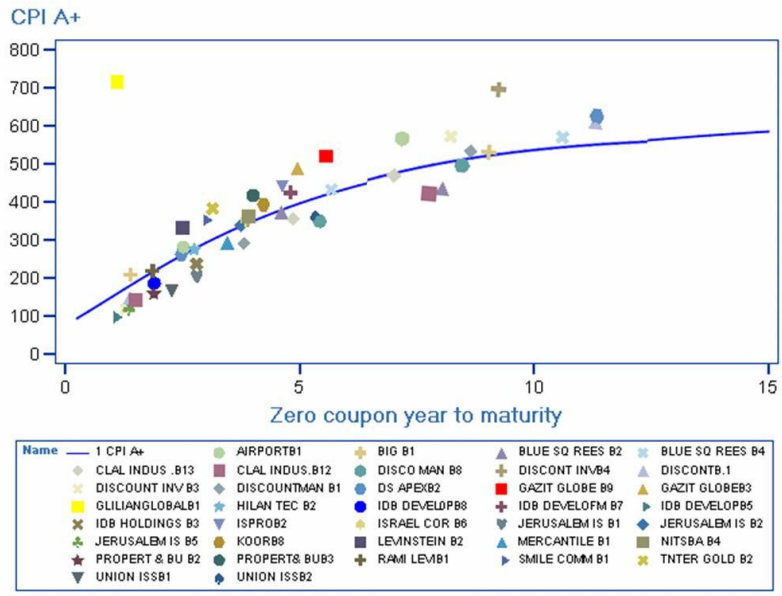


Figure 1: Weekly estimation of the "A+" rating class

Figure 1 illustrates the N-S estimation of the A+ rating class. The line illustrates the Fair Value computed yield. The assorted points illustrate the yield of each listed bond. The vectors are computed in the same manner from the Risk Free class to –A rating class.

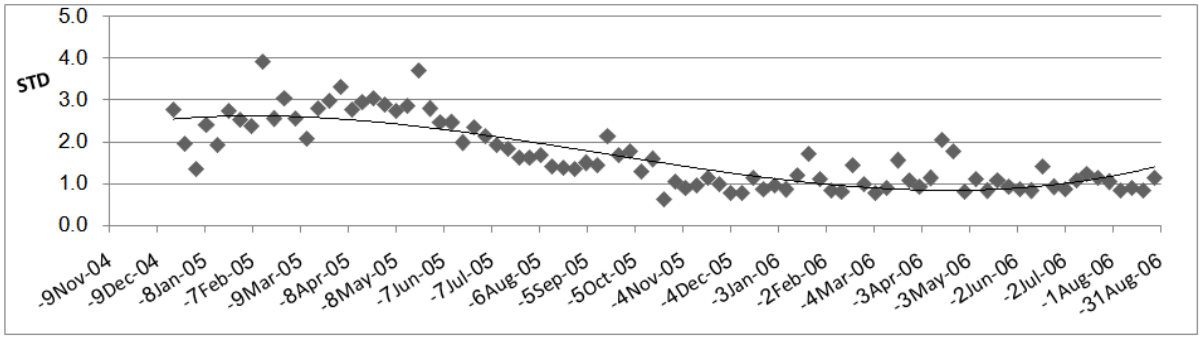


Figure 2b: "A" cluster variance convergence

Figure 3B illustrates the convergence of the variance tracking error of the A rating cluster over the sample period. On the Y axis is the standard deviation. Every point is a weekly sample. The trend line is a 3rd degree polynomial. The standard deviation of the A cluster falls from 3.1 to about 1.2, on average at the end of June 2006, before somewhat growing in July-Aug 2006.

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