Generalized Entropy Theory of Information And Market Patterns

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Abstract

We develop an economic theory of information generalized from the entropy theory of information and show that it provides the foundation to understand market behavior. One fundamental result from this information theory is that information with higher value is in general more costly. Another fundamental result from this information theory is that the amount of information one can receive is the amount of information generated minus equivocation. The level of equivocation, which is the measure of information asymmetry, is determined by the correlation between the source of information and the receiver of information. How much information one can receive depends on the background knowledge of the receiver. In general, industry insiders understand information earlier than other investors; large investors, who are willing to spend more to collect and analyze information, generally utilize different kinds of information from small investors. This heterogeneity in information processing by the investment public offers a simple understanding of the price and volume patterns uncovered in the empirical studies, which have been unable to be explained by the existing theories in behavioral finance.

Keywords: information, entropy, market patterns, behavioral finance
JEL classification: G14

The patterns of security markets reflect the patterns of information processing by the investment public. Understanding how investors process information is the key to understand market patterns. The standard economic theory of information was developed by Grossman and Stiglitz (1980). This theory is based on rational expectation. It assumes that investors can accurately assess the value of some information and pay some fixed amount accordingly to obtain the information. Recently, various models relax the rational expectation assumption to explain major market patterns. Most of these models rely on some kind of human psychological biases and are generally grouped under the category of behavioral finance. While these models can explain some of patterns, they are unable to explain other patterns. In this work, instead of modifying some assumptions from Grossman and Stiglitz's theory, we propose a new economic theory of information that is based on Shannon's entropy theory of information and show how this theory provides parsimonious understanding of major market patterns.

Shannon's entropy theory of information was originally developed in 1948 to solve technical problems in information transmission across communication channels. However physicists have been thinking about the relation between entropy and information for over a hundred of years. (Maxwell, 1871) In this work, we will show that several important properties can be derived from the entropy theory of information when it is applied to economics. First, information with higher value is in general more costly. This is a direct extension from Maxwell's (1871) thought experiment on an intelligent demon. Second, the amount of information one can receive is the amount of information generated minus equivocation. The level of equivocation, which is the measure of information asymmetry, is determined by the correlation between the source of information and the receiver of information. In general, how much information one can receive depends on the background knowledge of a person. Therefore the process of understanding information is a process of learning, which often takes long time. Third, the value of information is inversely related to the number of people who understand it. For example, an investor who buys the shares of a company before it becomes popular often earns higher rate of return than those who buy the shares of the same company when it becomes hot. At the same time, the value of a company's investment is also affected by how much its competitors understand the technology and market potential of a product. We will call this economic theory of information the generalized entropy theory of information, which, unlike other existing theories, is a non-equilibrium theory.

A new theory is ultimately justified by its implications. Empirical studies have uncovered many distinct patterns on security return and trading volume. (DeBondt and Thaler, 1985; Jegadeesh and Titman, 1993; Lee and Swaminathan, 2000; Hvidkjaer, 2001) Recently, several models are developed to explain some of these patterns. However, these models are based on some ad hoc assumptions and could not explain other distinct patterns. (Lee and Swaminathan, 2000; Hvidkjaer, 2001) In this work, we show how this generalized entropy theory of information offers a simple understanding of market patterns and resolves some of the puzzles about market patterns raised in the recent literature.

The remainder of the paper is structured as follows. Section I develop the generalized entropy theory of information. Information theory provides natural measures of the cost of obtaining information and of information asymmetry. Section II explains how the common patterns of security returns and trading volumes are natural results of information processing by the heterogeneous investment public. It also answers many questions on the gaps between existing behavioral theories and empirical evidences. Section III discusses how this information theory based model of investor behavior is related to other models of behavioral finance. Many assumptions in some of the recent theoretical models can be derived naturally from the entropy theory of information. Section IV concludes.

I. Generalized entropy theory of information

The value of information is a function of probability and must satisfy the following properties:

1. The information value of two events is higher than the value of each of them.
2. If two events are independent, the information value of the two events will be the sum of the two.
3. The information value of any event is non-negative.

The only mathematical functions that satisfy all the above properties are of the form

$$H(P) = -\log_b P \tag{1}$$

where H is the value of information, P is the probability associated with a given event and b is a positive constant. (Applebaum, 1996) Formula (1) represents the level of uncertainty. When a signal is received, there is a reduction of uncertainty, which is information.

Suppose a random event, X, has n discrete states, $x_1, x_2, \ldots, x_n$, each with probability $p_1, p_2, \ldots, p_n$. The information value of X is the average of information value of each state, that is

$$H(X) = -\sum_{j=1}^{n} p_j \log(p_j) \tag{2}$$

The right hand side of formula (2), which is the entropy function first introduced by Boltzmann in the 1870s, is also the general formula for information. (Shannon, 1948)

After the entropy theory of information was developed in 1948, its technique has been applied to many different problems in economic and finance. (Theil, 1967; Gulko, 2002; Maasoumi and Racine, 2002) In this work, we will expand the entropy theory of information to the area of human cognition by discussing the physical and economic cost of understanding information.

The concept of information has been intimately related to entropy for over a century. In a thought experiment, Maxwell (1871) reasoned, if information is costless, the entropy of a system can be decreased. But this would violate the second law of thermodynamics. Maxwell went on to conclud that the physical cost of obtaining information must be at least as much as the value of information. His reasoning also implied that information of higher value is of higher physical cost. Shannon (1948) identified information as entropy many years later, which makes the equivalence between information and physical entropy explicit. (Bennett,1988). Since economic cost is highly correlated to physical cost, (Georgescu-Roegen, 1971) more valuable information is in general more expensive to obtain.

Figure 1 is a graph of formula (1), where H is a function of P, the probability of any given event. From Figure 1, value is a decreasing function of probability. In information theory, P represents the probability some event will occur. In this work, P is generalized to represent the percentage of people or money that is controlled by informed investors. When $P = 1$, $-\log P = 0$. Thus the value of information that is already known to everyone is zero. When P approaches zero, $-\log P$ approaches infinity. Therefore, the value of information that is known to few is very high. For example, if an unexpected surge of corporate profit is going to occur, and is known to very few people privately, i.e., when P is very small and $-\log P$ is very big, then the information is highly valuable. Huge profit could be made by trading the underlying stocks. But if the information is announced publicly and becomes known to many people, then the value of this information is very low. Little profit could be made from trading on such information.

It is often said that the cost of information has dropped sharply over the years. But at the same time, the value of the same type of information has dropped sharply as well. Important and accurate information that is only known or understood by a few is carefully guarded precisely because of its high value. For example, Warren Buffett, who has a very successful record for gaining and using insightful market information, would not announce to the public which stock(s) he is going to buy or sell. The general public only finds out in the news when such large investors make significant moves in the marketplace.

Even when information is distributed freely, a receiver may not be able to comprehend its full meaning. Following Shannon (1948), the amount of information one can receive, R, would be equal to the amount of information sent minus the average rate of conditional entropy.

$$R = H(x) - H_y(x) \tag{3}$$

The conditional entropy $H_y(x)$ is called the equivocation. It measures the average ambiguity of the received signal. Originally, Shannon used this formula to discuss how noises affect the efficiency of information transmission. But it can be understood from more general contexts. The level of conditional entropy $H_y(x)$ is determined by the correlation between senders and receivers. When x and y are independent, $H_y(x) = H(x)$ and $R = 0$. No information can be transmitted between two objects that are independent of each other. When the correlation of x and y is equal to one, $H_y(x) = 0$. No information loss occurs in transmission. In general, the amount of information one can receive from the source depends on the correlation between the two. The higher the correlation between the source and receiver, the more information can be transmitted. So $H_y(x)$ offers the quantitative measure of information asymmetry. Since different people have different background knowledge about the same information, heterogeneity of opinion occurs naturally. To understand the value of a new product or new production system make take the investment public several years. To fully appreciate the scope of some technology change may take several decades. For example, the economic and social impacts of cars as personal transportation instruments and computers as personal communication instruments were only gradually realized over the path of several decades. This is why individual stocks and whole stock markets often exhibit cycles of different lengths.

From above discussion, the entropy theory of information, when applied to human cognitive processes, has the following properties. First, information that is more valuable is in general more expensive to obtain. Second, the amount of information one can receive depends on the person's background knowledge about that particular information. Third, the same information, when known to more people, becomes less valuable. This economic theory of information may be called the Generalized Entropy Theory of Information. It differs from the standard Grossman-Stiglitz information theory and its recent extensions in behavioral finance in several aspects.

First, it is directly derived from fundamental physical laws, which all human activities conform to. So it is built on a more solid foundation than the rational expectation theory and its ad hoc adjustments. That is why this theory offers a simple understanding of human information processing. For example, the assumptions of some recent models in behavioral finance can be derived naturally from this generalized entropy theory of information. Second, it is a non-equilibrium theory. It does not assume a company possesses some intrinsic value waiting to be discovered by the investment public. Instead, the process of understanding the value of a company by the investment public is accompanied by the process of understanding the technology and market potential by its competitors, which generally reduce the value of that particular company. (Chen, 2002) Empirical results that we will analyze later support this statement. It is well known that the most fundamental property of living systems is that we are non-equilibrium systems. (Prigorgine, 1980) Therefore, a non-equilibrium theory of human economic activities is consistent with this most fundamental property, while the general equilibrium theory, though logically consistent, is not. This is why the model based on non-equilibrium thermodynamic theory offers much simpler understanding of market behaviors than those on equilibrium theory.

In the next section, we will apply the generalized entropy theory of information, a theory based on most fundamental physical laws, to understand the patterns in the stock market without directly invoking assumptions on human psychology. This will avoid the problem of overfitting theories to empirical observation.

II. The patterns in financial market

The patterns of security markets reflect the patterns of information processing by the investment public. To an investor, the choice of information gathering is a matter of cost. More valuable information is more costly to obtain in general. For large investors, it pays to spend a lot of effort and money to research the fundamentals. For small investors, it doesn't pay to dig into the fundamentals. They depend on processed and easy to understand information that is readily available at low cost, such as news from popular media and price movement of the shares. When an investor will be able to access a certain information also depends on her particular background, which determines her level of equivocation in receiving that information. In the following, we will illustrate the patterns of return and trading volumes of a stock of a typical company from the information processing cycle, which is similar to Lee and Swaminathan's (2000) momentum life cycle hypothesis.

Suppose a company develop a new technology, which is expected to bring the company high profit in the future. From (3), those who are familiar with the technology and company will have low equivocation in receiving the information. They understand the significance of the information first and buy the company shares. Since they are a small number of people, the buying is of low volume. This corresponds to the beginning of the low volume winner stage in momentum life cycle. From table IX of Lee and Swaminathan (2000), the return on equity does improve over the next three years for low volume winner, which shows that the investors in this stage do have accurate perception about the future. From Figure 5 and 7 of Hvidkjaer (2001), the buying pressures from both large trades and small trades in this period trend up gradually, signaling the gradual diffusion of information. The buying pressure from large trades are always higher than the buying pressure from small trades, which shows that large traders as a group are better informed than small traders.

As the technology goes through various stages from R&D to production, the potential becomes clearer to more people. This means that the level of equivocation gradually reduces to more people, which sustains buying interest and share prices increase gradually. As the technology becomes adopted in production and profit figures become public, the level of equivocation decrease further and the pool of investors increases further. Eventually, both the sustained increase of stock price and stable pattern of profit increase, which are very easy to understand by the general public, attract large amount of buyers, which results high trading volume and push the stock prices further up. This corresponds to the high volume winner stage in momentum life cycle. From Figure 6 of Hvidkjaer (2001), there is a steady and higher buying pressure among large traders than in low volume winner stage, signaling a consensus of bullish sentiment from informed investors. Because of this consensus, the return of this stage is extremely high. (Lee and Swaminathan, 2000, Table IV) From Table IX of Lee and Swaminathan (2000), the return on equity is very high for high volume winners. However, the high return of the company will attract the attention of not only investors but also competitors, which will try to produce same or similar products for this high profit market.

From Figure 1, the value of some information that is known to everyone is zero. As the good news reaches most investors, the security is probably already fully or over priced. Among the increased pool of investors, more and more investors understand very little of the fundamentals behind the technology and depend on easy to understand signals such as coverage from popular media and stock price movement to make trading decisions. For this group of investors, they will stop buying only when the opinion of public media changes and the trend of price increase reverses significantly. As stock price keeps increasing, momentum trading becomes highly profitable, which will eventually push the share prices higher than the fundamental value. Since large investors spend more resources in investment, they are generally better informed than small investors. As share prices become highly overvalued relative to fundamentals, large investors start to unload positions while small investors keep buying. As the selling pressure from large investors becomes greater than the buying pressure from small investors, the trend of price increase reverses to price decrease. (Hvidkjaer, 2001, Figure 6 and 8) This is the period of high volume losers in momentum life cycle. In the period of high volume loser, as competition intensifies, return on equity drops sharply from previous years. (Lee and Swaminathan, 2000, Table IX).

As the pattern of price drop becomes clear, more and more people joined the selling. After large investors and some of the small investors have finished unloading the positions, the volume of trading will decline, which is the period of low volume loser in momentum life cycle. This period is characterized by active selling of small investor. (Hvidkjaer, 2001) Since small investors are typically slow to understand information, their active selling, after the selling by large investors, signals the selling is overextended, which indicates the low volume losers will rebound and earn high future return in general. From the operation point of view, this is the worst time for the company. Overcapacity of a once high profit margin industry pushes down the return on equity further from the high volume loser stage. There are probably some layoffs of labor and write off of capital. But the return on equity will gradually regress toward normal level. (Lee and Swaminathan, 2000, Table IX).

The above paragraphs describe the patterns of information processing and trading when the initial news is positive. When the news is negative, a similar pattern exists at opposite directions. Since there is a cost shorting stocks and there are many institutional constraints on shorting stocks, short selling is much more difficult than buying stocks. With good news, there are many potential buyers. With a bad news, the sellers are largely confined to existing share holders. So overreaction is less strong on bad news. The statistical results, which are the average of all phenomena, mainly reflect the action from good news instead of bad news. With this observation in mind, we can discuss the following:

“The Hong and Stein (1999) model predicts that momentum profit should be larger for stocks with slower information diffusion. If we make the assumption that scarcity of trading leads to insufficient diffusion of information, then the Hong and Stein model would predict a greater momentum effect among low volume stocks. Our result indicate this to be true among winners but not among losers. That is, low volume winners have greater momentum, but low volume losers actually have less momentum." (Lee and Swaminathan, 2000, p. 2062)

The information theory indicates that low trading volume may reflect either a lack of understanding of some new information or a lack of information. From the above discussion, there are two types of low volume losers. The first, which is an average representative from Lee and Swaminathan's statistical results, is part of a cycle that is triggered by some good news. It has experienced the cycle of low volume winner, high volume winner, high volume loser and low volume loser. The low volume loser period represents the end of an information processing cycle. This is why it exhibits less momentum. The other type is the low volume loser period at the beginning of an information processing cycle that is triggered by a bad news. (Hong, Lim and Stein, 2001) These low volume losers do exhibit strong momentum in low rate of return. So the apparent inconsistency of both views can actually be reconciled with a more detailed analysis from information theory.

The analysis of information processing cycle helps answer two of the questions or surprises in Hvidkjaer's work. One question is that why small traders are consistently late-stage momentum traders. From our analysis, small traders adopt low cost information gathering strategy. They depend on processed and easy to understand information that is readily available at low cost, such as news from popular media and price movement of the shares. It is only after some companies are doing very well or very bad for a long time that popular media begin to discuss these companies, which attract the attention of small traders. The stocks of these companies generally have long term upward or downward trends, which are easy to spot by small investors. The dependence on low cost information by small traders explains why they are consistently late-stage momentum traders. This analysis also answers why there is an intense small-trade buying pressure among high turnover losers, which Hvidkjaer termed as "the most surprising result of the paper". Since high turnover losers are recent losers with extremely good past performance, the media are generally optimistic about their future. The recent price drop or "profit taking" creates "attractive buying opportunities", as often reported in news media. Since small traders generally don't have enough information to determine the fundamental values of companies, there is no easy way for them to tell if a company is overpriced.

What determine the level of underreaction and overreaction? It depends on how much we understand the fundamentals. If the fundamentals are easy to understand by many people, both initial underreaction and eventual overreaction will be small. If the fundamentals are difficult to understand, mispricing can be substantial. We can have a look at glamour stocks. Glamour stocks are from companies with high earning growth. This means they have very few potent competitors, which generally indicates the lack of deep understanding about the particular products or production systems. That is to say, there is a high level of information asymmetry between the companies of glamour stocks and the general public. Initially, these types of companies are underpriced because few people understand them. However, the solid earning growth of these companies makes the share prices grow continuously, generating clear technical signals. The clarity of technical signals and vagueness of fundamental information will eventually cause high level of overreaction. Statistical results show that stocks undergoing price momentum over longer period will exhibit higher level of reversal. (Lee and Swaminathan, 2000, Table I) Economy wide, great speculative bubbles are generally associated with "new era" or "new economy", when the general public are touched by the profound influence of technology breakthroughs while having little understanding of the underlying mechanisms. (Shiller, 2000)

In the following, we will answer the three questions posed by Lee and Swaminathan at the end of their paper.

"First, the asymmetry in the timing of momentum reversals between winners and losers remains a puzzle. We show that low volume losers rebound quickly and outperform high volume losers with the next three to 12 months. However, it takes low volume winners longer (more than 12 months) to significantly outperform high volume winner. We know of no explanation for this timing difference." (Lee and Swaminathan, 2000, p. 2067)

From our analysis of information processing cycle, the low volume winner stage is the gradually understanding of fundamental news about a firm. Since the understanding of fundamentals is very costly and generally take very long time, it will take long time for low volume winners to significantly outperform high volume winners. The high volume loser stage is when large investors are already well informed about the overpricing and are active sellers. The price at this stage is supported by active buying of small investors, which mainly respond to popular media coverage and technical signals. (Hvidkjaer, 2001) Since coverage from popular media and technical signals, which are information with low cost and low value, are easier to understand than details about fundamentals, the price adjustment at this stage is much faster.

"Second, with the possible exception of the disposition effect from the behavioral literature, we know of no explanation for why trading volume should decline when firms fall out of favor."

The volume of trading reflects how many investors believe they can make profitable trades. When stocks are out of favor, few people believe they can make a profit buying these stocks. Hvidkjaer's detailed analysis shows that losing stocks do experience consistent selling pressures over a long period of time. The low volume of trading when firms fall out of favor reflects one fundamental asymmetry in security trading. For a stock, there are always more potential buyers than potential sellers, who are largely existing share holders.

"Finally, we find it remarkable that measures as readily available as past returns and trading volume can have such strong predictive power for returns. … Why this information is not fully reflected in current prices is another puzzle we leave for future research."

From (3), how much information we can understand depends on our background knowledge about the information and how much weight we assign to the information. From the efficient market theory, trading volume carries very little information. So little weight was given to the idea that trading volume might contain valuable information, which inhibited the research on this direction in the past.

III. The relation with other models of behavioral finance

Recently, several behavioral models provide frameworks to interpret the short to intermediate term momentum and long term reversal of return. In this section, we will discuss the relation of the Generalized Entropy Theory of Information with these models. Daniel, Hirshleifer and Subrahmanyam (1998) explain momentum in terms of both initial and delayed overreaction, while Barberis, Shleifer and Vishny (1998) and Hong and stein (1999) explain momentum in terms of initial underreaction and followed by delayed overreaction.

From the information theory, the absorbing of a new information is a gradual process, in which the equivocation gradually reduces. So stock prices generally undereact to new information initially, which is confirmed by empirical evidences. (Hvidkjaer, 2001) This is consistent with the models of Barberis et al. (1998) and Hong and stein (1999). In the following, we will make further analysis of these two models.

Barberis et al. (1998) utilize the concept of conservatism to understand underreaction. Conservatism states that individuals update their beliefs slowly in the face of new information. This property is a natural result from (3), where equivocation reduces gradually. Barberis et al. (1998) attribute overreaction to representativeness heuristic. "People rely on a limited number of heuristic principles which reduce the complex tasks of assessing probabilities and predicting values to simpler judgmental operations." (Tversky and Kahneman, 1974, p.1124) Many investors don't want to spend tremendous resource to research fundamentals. They rely on a limited number of heuristic principles, such as technical signals and opinions from popular media, which reduce the complex tasks of assessing probabilities and predicting values of stocks to simpler judgmental operations with low cost. As we analyzed in the last section, this reliance on simple heuristic principles leads overreaction in the asset market.

Hong and Stein's (1999) results are built on three key assumptions. The first two assumptions are that traders are classified as "newswatchers" and "momentum traders" according to their information processing abilities. They commented that, "the constraints that we put on traders' information-processing abilities are arguably not as well-motivated by the experimental psychology literature as the biases in Barberis et al. (1998) or Daniel et al. (1998), and so may appear to be more ad hoc." (Hong and Stein, 1999, p. 2145) These assumptions can actually be derived naturally from the entropy theory of information. Depending on the value of assets under management, different investors will choose different methods of information gathering with different costs. "Newswatchers" are large investors who are willing to pay a high cost to collect private information and to make a deep understanding of public information. "Momentum traders" are investors who spend less cost or effort on information gathering and rely mainly on easy to understand low cost information such as coverage from popular media and price momentum signals. Cohen, Gompers and Vuolteenaho (2002) show that institutional investors buy on fundamental news while individual investors buy on price trends. The third assumption of Hong and Stein (1999) is that private information diffuses gradually across the newswatcher population. The gradual diffusion of private information means that the number of people who enjoy low level of equivocation on some information gradually increases.

Both the reduction of equivocation of a representative investor and the increase of number of investors who have low level of equivocation on information contribute to the gradual reduction of underreaction, which generates momentum. Both representativeness heuristic and "momentum trader" can generate overreaction, which will lead to eventual reversal. The information theory can further distinguish the models of Barberis et al. (1998) and Hong and stein (1999). In Barberis et al. (1998), a representative investor make trading decisions. In Hong and stein (1999, 2003), investors are heterogeneous. From (3), investor heterogeneity can be understood naturally because of the different background of the investors and different cost that different investors are willing to pay to gather information. Empirical evidences show that investor heterogeneity exists in financial markets and plays an important role in the formation of trading patterns. (Hvidkjaer, 2001)

From (3), the understanding of information depends on the background knowledge. Investors take longer time to understand information from sources they are less familiar with. Hong, Lim and Stein (2001) empirically confirm that information from small firms, from firms with low analyst coverage and from firms with bad news, which managers are reluctant to release, generally diffuse slower. From Hvidkjaer (2001), the selling pressures on loser generally are stronger and last much longer than buying pressures on winners, suggesting information processing is less efficient on bad news.

After discussing the existing behavioral models, Lee and Swaminathan summarized, "existing theories of investor behavior do not fully account for all of the evidence. … none of these models incorporate trading volume explicitly and, therefore, they cannot fully explain why trading volume is able to predict the magnitude and persistence of future price momentum." (Lee and Swaminathan, 2000, p. 2066) Trading volume, on the other hand, is an integral part of the model of investment behavior based on the Generalized Entropy Theory of Information. This model answers many questions on the gaps between existing theories and empirical evidences.

IV. Conclusion

In this work, we develop the Generalized Entropy Theory of Information, which is a direct extension of Shannon's entropy theory of information to the context of economic and social activities. We show that the theory provides a simple understanding of the patterns of the security markets.

This work does not explicitly discuss how investor biases and irrationality affect the pattern in asset markets. However, it will help the rigorous investigation on the relation between human psychology and market patterns. First, since many patterns in asset markets can be explained by the Generalized Entropy Theory of Information directly, the focus of attention can be directed to search the links between human biases and the phenomena or magnitude of phenomena in asset markets that could not be explained by the information theory. Second, human activities, including mental activities, are constrained by physical laws. (Chen, 2003) These constraints offer initial tests to the plausibility of many assumptions. For example, from the information theory, new information can only be understood gradually by human beings. If a behavioral theory suggests investors will generally overact to new information, we need to examine the empirical evidence with great caution.

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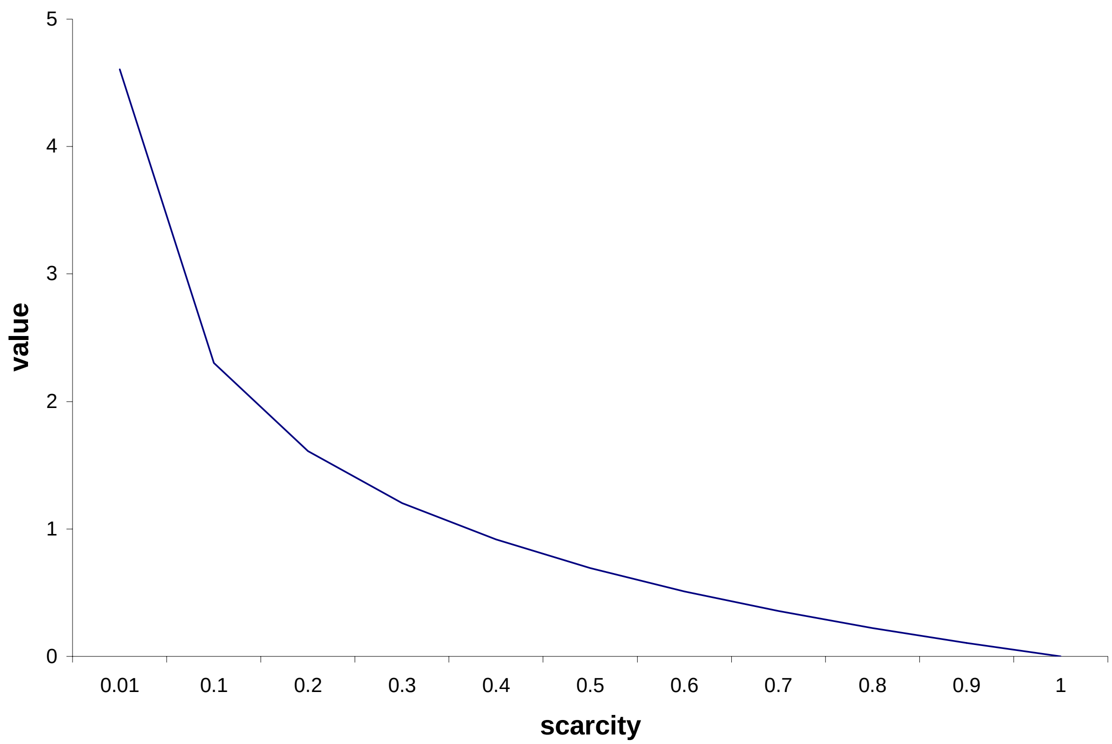
Figure Captions

Figure 1: Value and scarcity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