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Are online auction markets efficient? An empirical study of market liquidity and abnormal returns

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ABSTRACT

Technological advances have facilitated investment in collectibles through online auction markets, where information regarding product characteristics, current and historical prices, and product availability is available to millions of market participants. However, market inefficiencies may still exist, where prices do not reflect market information and where savvy speculators can profit. Using *unit root and variance ratio tests*, we examine 8538 rare stamp and 56,997 rare coin auctions to evaluate the *efficiency of online markets*. In particular, we study *market liquidity*, *abnormal returns* and *weak-form efficiency*. We find an inverse relationship between market efficiency and liquidity. Bidder competition intrinsic to liquidity increases the chances that uninformed bidders drive up item prices, leading to the observed market inefficiencies.

1. INTRODUCTION

It is common knowledge among investors that thin markets are less efficient than markets that have broader following and participation. Many housing markets, some stock markets, mortgage-backed securities markets, and collectible markets represent examples of thin markets, where purchase and sales transactions, trading, and exchange may be sporadic, and price discovery may be challenging. Together, nevertheless, they represent billions of dollars of exchange in market transactions. Increasingly, we are seeing relatively thin markets being impacted by the burgeoning technologies of the Internet, permitting such innovative approaches to transaction-making as electronic call auctions, reverse auctions, and numerous forms of digital intermediation.

With so much price information available to bidders and sellers in online auctions, the question of market efficiency in these collectible markets presents itself. By market efficiency, we mean that the market price is based upon all information available in the market. From this perspective, weak-form efficiency in a market occurs where the price for every good on the market reflects all historical information, and is available to any market participant [13]. Market efficiency is different from operational efficiency in that it deals with equal access to information by all market participants. By contrast, operational efficiency deals with maximizing some aspect of the operation, with little concern about the transfer of information among all participants in the market. For example, Vragov [49] discusses how online auctions are operationally efficient in that they allow the seller to maximize common and private value surplus.

Intermediaries utilize technology to bring together geographically-fragmented markets, as a way to improve financial efficiency and market quality. These markets exhibit the classical characteristics of thin markets. We investigate the efficiency and persistence of abnormal returns in collectible markets. Collectibles are often viewed as an investment alternative, which can be used for diversification or as a hedge against inflation (like gold bullion) with some rare coins even quadrupling in value after several years. Swiatek [47] discusses how rare coins can be appealing in a bear market, and Pesando [41], Mei and Moses [37], and Wood [50] compare collectible returns to stock market prices using financial economics theory, like the capital asset pricing model (CAPM). Ashenfelter and Graddy [4] also point out research that shows returns on collectible items can surpass returns from fixed income securities.

Typically, auctions have not been viewed as very efficient markets, as an uninformed bidder could end up paying too much for an item or a seller could end up selling an item for a fraction of its worth [43] and [48]. Internet technologies, however, have increased the flow and availability of information in online auctions, allowing millions to interact, and promoting participation across the globe. This technological transformation has made auctions into a type of exchange, akin to a stock or commodities exchange. Indeed, the volume of transactions in online auctions now surpasses the volume of stocks that are bought and sold in many countries. With many more items for sale, and many more bidders bidding, online auctions allow collectibles as investments to take on a new practicality, making investments in collectibles bought and sold in online auctions more feasible for the typical investor. Through this lens, we investigate how efficiency has adjusted with market liquidity, as more buyers and sellers have entered the online auction market and the ratio of buyers to sellers has changed.

Abnormal returns occur when price levels differ from expected or previous sale prices, resulting in high or low returns for an investor. They occur due to new information in the market. Abnormal returns in an efficient market are persistent, indicating that other investors share a new common valuation, whereas an inefficient market with low levels of persistent returns indicates that abnormal returns are ignored. Then prices revert back to the mean price after the abnormal return occurs. We do not deny that under-informed bidders may make bids that may be too high, yet the existence of high bids is likely to inflate the price that rational and informed investors will be wiling to pay for an asset.

In efficient markets, abnormal returns reflect new information, so that abnormal returns in one period carry forward to future prices. In inefficient markets, the effect of abnormal returns are often minimized or eliminated, as prices revert to a mean price. With this in mind, we will not claim that online auctions, in their current form at least, can ever be viewed as completely efficient markets. We will explore the persistence of abnormal returns to determine how much current returns seem to affect the level of future returns. We will check if future returns are unpredictable, as they would be in an efficient market.

We ask: Are online auction markets, such as those for rare coins and rare stamp markets, efficient? What factors might affect the persistence of abnormal returns in online auctions? How can we measure the efficiency and persistence of abnormal returns on assets traded in online markets? Can we implement a research design to assess the efficiency and persistence of abnormal returns in online auctions for collectible coins and stamps? How does the amount of trading activity play a role?

There are major differences between a stock market, where market efficiency is typically studied, and an online auction market. The first difference deals with short selling, where investors can take advantage of an overpriced stock by selling the stock now and agreeing to buy it later. There is no way to easily mimic short selling in online auction markets, thus allowing inflated prices to persist. A collectibles investor is able to place an item for sale, and then purchase it in the same market later, but the immediacy of the stock market is not present. The second difference deals with the effects of individual bidders. Unlike the stock market, two bidders can drive a price above the normal valuation for an item. (This is a basis for winner's curse in online auctions.) These two factors can introduce inflated prices for an item, as two or more bidders bid up its price, resulting in high prices that may persist for the sale of the item in the future.

Far from making inefficiency irrelevant though, the differences between online auction markets and stock markets make studying efficiency imperative for investors. Online auctions have challenges that stock markets do not. Since investors make money by taking advantage of inefficiencies, these inefficiencies can make online auctions potentially more profitable than stock market investments. We will expose inefficiencies that may exist in online auction collectible markets for the investor to exploit. To do this, we provide a measure of weak-form efficiency in online auctions for collectibles, and confirm a relationship between market efficiency and market liquidity in the rare coin and rare stamp markets. Thus, increases in market liquidity (marked by an increase in bidder competition) lead to decreases in online auction market efficiency. The theoretical intuition that drives this finding is that, with stock markets, increase in the number of investors would indeed lead to greater efficiency as more investors search to profit from inefficiencies. By contrast, in online auctions, high liquidity involves many bidders competing for the same item. It increases the likelihood that uninformed collectors drive up collectibles prices.

We draw upon theory in financial economics for this work. IS researchers are often concerned with how information is transferred among participants in online systems, and the effects this information has on system users. This becomes especially interesting when the system is a market, and the market is created with the new technologies of the Internet. We leverage the theory of market efficiency to discover the effects of the flow of information on prices in an electronic market.

We assess online auctions for collectible coins and stamps as a type of market exchange. We focus on rare coins and stamps that are commonly traded. We treat instances where the amount of trading and transaction-making varies, permitting us to consider what happens in online markets with more thinly-traded assets. Our research design enables us to investigate how the persistence of abnormal returns increases with market liquidity, as the ratio of buyers to auctions changes in online auction markets. This lets us determine how market liquidity may affect efficiency and the persistence of abnormal returns based on the price changes. Using unit root tests attributable to Dickey and Fuller [16] and variance ratio analysis based on Lo and MacKinlay [33] on data from a multi-year study involving two different markets, we show that online markets tend to be efficient if the number of auctions is relatively large in relation to the number of bidders. Although trading in online auctions is thinner than in the stock markets, we nevertheless find that online auctions increase the viability of investments in collectibles as an alternative to stocks because of their wide reach and the extent of seller and bidder participation.

Section 2 assesses relevant theory for thin markets and technology, collectible auctions, and the related concepts of market efficiency, as a basis for our model development. Section 3 discusses the specification of unit root and variance ratio tests, as well as some adjustments that enable us to estimate our data for relatively thinly-traded collectibles exchanged in online auctions. Section 4 lays out our empirical analysis of a large set of data on collectible coins. We begin with an overview of the data set, continue with a discussion of modeling and estimation issues that are specific to a market (e.g., the rare coin market or the rare stamp market), and finish with a presentation of the econometric results and their interpretation. Section 5 discusses the collectible stamp data that we analyze, and the contrasting results that we obtained. Thereafter, Section 6 provides an interpretation of our results, and analyzes the patterns of abnormal returns observed in the collectible coin and stamp markets. We conclude with limitations and future research.

2. ONLINE AUCTION MARKETS AND MARKET EFFICIENCY

We next discuss properties of thin markets, collectibles auction, and market efficiency concepts.

2.1. Thin markets and technology

Certain factors that exist in markets can cause inefficiencies. For example, the depth of the market is often limited by the degree to which assets are traded in different physical, geographic, or electronic virtual locations, causing market fragmentation. Also, Mendelson [38] points out that market fragmentation can occur when potential market participants cannot find one another, do not know that the other party exists, or otherwise cannot transact because of spatial, informational or other types of barriers. When there are relatively fewer traders in a market with thinly-traded assets, the market is more likely to be fragmented. The trading of securities before the advent of the telegraph is a classic example of fragmented markets, as discussed by Garbade and Silber [23]. Securities traded at vastly different prices at different stock exchanges around the United States because information could not travel between the exchanges quickly. The telegraph, a technological innovation with sweeping and dramatic effects, almost immediately brought together geographically-separated markets, bringing greater similarity in prices. Just as technology was able to close the information gap in geographically-fragmented but relatively deep markets, so technology can help market participants to find one another in markets where assets are more thinly traded. When the markets consolidate, market prices will better reflect information that is known to all participants across the space that the market can cover.

Markets with thin trading of assets are more likely to be volatile than deeper markets, all else equal, due to the lack of price discovery [46]. At the heart of efficiency studies is the availability and transfer of accurate information about an asset. Transaction-making provides a basis for information to be exchanged by sellers and buyers about price levels that are appropriate, so when there are fewer transactions, as with traditional offline auctions, it becomes more difficult to determine the appropriate price. Although stock markets, with millions of traders per day, will always have more transactions than online auction markets, at least for the foreseeable future, Internet technology has given online auctions a large increase in market depth with the ability to transfer information on millions of transactions that allow much information to transfer among buyers and sellers. This reduces market fragmentation and allowing analysis of online auction transactions at a new level and giving online auction researchers the ability to analyze online auctions using well-developed financial tools.

2.2. Private valuation and common valuation

Private values arise from a collector's personal valuation for an asset that is not shared by the rest of the market. For example, if the next coin or stamp they target completes a collection, then the collector may be willing to pay more for the item. With no common valuation, financial economics topics such as efficiency become moot since private valuation affects bid levels rather than commonly-held information. Although many contend that private valuation almost always exists in collectible markets, recent research from Bajari and Hortaçsu [5] and Easley et al. [19] empirically demonstrate that there is a significant common value component to online auctions of collectibles, specifically rare coin online auctions. Their results show that although private valuation may (and probably does) occur in online auctions, the common valuation component is powerful enough to allow coin bid levels to be compared across bidders and across auctions.

We have examined common and private valuation in online auctions in two ways. First, we have implemented Bajari and Hortaçsu's [5] technique and have supported their finding that a significant level of common valuation exists in our collectible data, such that the level of valuation attributable to common valuation significantly exceeds the level of valuation attributable to private valuation. Second, we have conducted unit root tests which show that private valuation has no significant impact on our results. Thus, we are confident that common valuation dominates the online coin and stamp auction markets. Analysis of these markets can be achieved by using existing empirical tools for financial economics.

2.3. Theoretical perspectives on market efficiency

Samuelson [44] developed the efficient market hypothesis, which contends that markets, like the stock market, tend to reflect all information that market participants have available. Because stock prices in an efficient market reflect all available information, no one can accurately predict which stocks outperform or underperform in the next period in an efficient market. Unexpected or abnormal returns in one period persist into all later periods, and it is impossible to predict whether the price will rise or fall, even after an abnormally large price increase or decrease. Furthermore, efficiency is the result of savvy investors who scour the market searching for inefficiencies, recognizing that asset prices that do not reflect all available information. This can lead to exceptional profits, and prices of investments automatically self-correct based on new information. Thus, even if a multitude of investors are inexperienced and prone to mistakes, an efficient market will force the price to reflect all available information.

The efficient market hypothesis has been widely researched as it applies to the stock market [3], [22], [25] and [28]. Boudoukh et al. [8] have noted that there are large and statistically significant autocorrelations and serial cross-correlations between portfolio returns over a short horizon. This goes against the efficient market hypothesis. Some researchers maintain that these correlations do not inform investors in any meaningful way, so that the aim of market efficiency is furthered. For example, research in the early 1960s [2], [12], [26] and [29] mostly provided strong support for the hypothesis that stock investments follow a random walk, which gave securities analysts no basis to predict prices from one period to the next. Fama [20] discussed how, in tests of the random walk, researchers by and large are unable to statistically reject the efficient market hypothesis (also called the random walk hypothesis). However, in a later article, Fama and French [21] rejected the random walk model on the basis of analysis of additional data.

More recently, Malkiel [36] commented on new findings on autocorrelations and serial cross-correlations for short horizon returns. He claimed that data mining that has been performed in some studies has resulted in findings that are surprising but still spurious, for example, the work of Lo and MacKinlay [33]. Also, he suggests that reviewers of papers at the leading journals have tended to set aside confirmatory results as lacking surprise value, while more surprising results that show deviations from a random walk may be more readily accepted in peer review, leading to a disconfirmation bias of existing theory. Malkiel further argued that any statistically significant variation from a random walk is not significant in a practical sense. Any gain that can be acquired from taking advantage of market inefficiencies is so small so as to not exceed the operational costs involved in adjusting an investment position.

Lo and MacKinlay [32] and [33] have argued that unit roots are neither necessary nor sufficient for random walk efficiency tests, based upon Fama's [20] definition of efficiency. These authors and others have shown that efficiency is a unit root only under the assumption of risk neutrality [30], [31] and [34]. Lo and MacKinlay [33] stress that risk-averse investors will have a well-functioning efficient market, and prices that can be forecasted in an efficient market, only such that the market reflects all available information.

Research on financial markets divides market efficiency into three categories [7] and [13]. Weak-form efficiency occurs where excess returns cannot be estimated using historical financial information. Semi-strong form efficiency exists where market prices reflect all publicly available information. Strong-form efficiency ensues when market prices reflect all publicly available and privately held information. We will examine collectible coins and stamps, and focus only on whether it is possible to estimate returns based on historical financial information. We do not address news items about new finds or the scarcity of coins and stamps, due to the limitations that we faced with the collection of relevant data. Thus, we examine weak-form efficiency.

We theorize that market liquidity has the opposite effect in stock markets as in online auctions. Liquidity implies that there are more buyers bidding on the assets in an exchange. In stock markets, informed bidders bid up an under-valued asset and bid down an overvalued asset through short selling. This permits an investor to sell at item immediately at an overvalued price and to buy it at a later date. Higher liquidity implies that there is a greater probability of two informed investors entering a market to drive the price to an efficient level.

The absence of short selling in online auctions makes market liquidity have the opposite effect on online auction market efficiency. By definition, a highly liquid item has a large number of potential bidders, resulting in an increased chance that two uninformed bidders will bid up an item. With no short-selling mechanism though, there is no way for informed bidders to bid down an overpriced asset in online auctions. So even though we agree with the literature in that market liquidity has a positive effect on market efficiency in stock markets, we contend that the absence of short selling in online auctions should add inefficiencies to online auction markets and cause market liquidity to have an inverse relationship.

3. METHODOLOGIES FOR ESTIMATING EFFICIENCY IN ONLINE MARKETS

We investigate market efficiency and the persistence of abnormal returns related to asset price differences over time in the collectible coin and stamp markets. We next illustrate the use of unit root tests to examine returns to stamp and coin trading, similar to Fama's [20] investigation of efficiency in the stock market. Such tests enable us to deliver a new reading on the persistence of abnormal market returns, as discussed by Grossman and Stiglitz [24], that may exist for collectible coin and stamp trading at various points in time in Internet markets. Our goal is to determine how market liquidity, as measured by the ratio of buyers to auctions, may affect a traded asset's returns, based on past patterns of returns in online auctions for collectible stamps and coins. We develop empirical models to address econometric challenges of measuring efficiency in markets that exhibit thin trading of assets.

3.1. Market efficiency tests using unit roots

To examine the effects of market liquidity on the degree of efficiency and persistence of abnormal returns in online coin and stamp auctions, it is necessary to define each collectible *i* in terms of the percentage of the price that obtained during the first time it traded relative to a later period *t*. We then evaluate the return on each traded asset based upon $P_{it} = \frac{price_{it}}{price_{i1}}$ and $\Delta P_{it} = P_{it} - P_{i,t-1}$, so that:

$$R_{it} = \left(\frac{P_{it}}{P_{i,t-l}} - 1\right) = \left(\frac{\Delta P_{it}}{P_{i,t-l}}\right) \qquad (1)$$

where

$price_{it}$	the final selling price for the collectible item *i* on day *t*;
$price_{i1}$	the average price for the collectible item *i* on the first day that it sells;
P_{it}	the indexed price for the collectible item *i* on day *t*;
ΔP_{it}	the indexed price change for the collectible item *i* on day *t* compared to the previous selling price at time $t - l$;
R_{it}	the percentage return for the collectible item *i* on day *t*.

Malkiel [35] and [36] initially presented the idea that future returns on market-traded assets are not predictable from past price performance in an efficient market. Thus, prices in efficient markets should follow a random walk. Consider the following autoregression function of asset returns:

$$R_{it} = \alpha_i + \beta_i R_{i,t-l} + \varepsilon_{it}. \qquad (2)$$

This expression is a *unit root test for stationarity*, as advocated by Dickey and Fuller [16]. The *estimated change in returns*, R_{it}, on asset *i* in the current period *t* are defined as a function of returns in a previous period $t - l$, plus a *drift parameter* α that is specific to asset *i*. The parameter, β_i, can provide information on whether returns for asset *i* are predictable based on previous returns. β_i can be expressed as:

$$\beta_i = \frac{cov(R_{it}, R_{i,t-1})}{\sigma^2(R_{i,t-1})}. \quad (3)$$

Malkiel [36] contends that a random walk occurs when $\beta_i = 1$. He further describes how returns based on random walks characterize an efficient market. He goes on to note that various stock market anomalies, such as the 2000 dotcom bubble burst, were devastating because they were not anticipated. This adds support for the random walk model as a test of the efficient market hypothesis.

If $\beta_i - 1$ is significantly different from 0, then β_i will be significantly different from 1, and there will be a predictable drift in returns rather than a pure random walk. Note that β is not the same as that used in risk-return models such as CAPM. However, the parameter is consistent in its use relative to other tests of the Dickey–Fuller method when a unit root test is implemented. With β_i close to 1, price changes are persistent, and thus current price changes are reflected in prices well into the foreseeable future. When $\beta_i = 1$, our best estimate of R_{it} is drift parameter α_i plus the return in the previous period $R_{i,t-1}$. Though we have an estimate, we have no way to know whether the return in this period will outperform or underperform that expectation. As β_i approaches zero, prices more immediately revert to a mean price, and price changes do not persist.

3.2. Market efficiency tests using variance ratios

Lo and MacKinlay [32] and [33] and Cochrane [10] have suggested that a *variance ratio test* is more appropriate than a unit root test to determine if a series follows a random walk. They state that for a random walk of asset returns to exist, such as those that might be seen for returns on certain investments, the variances of the returns must be uncorrelated. Moreover, they state that the asset return variances should be consistent across periods for any traded asset if market efficiency is thought to exist. See Lo and MacKinlay [33] for additional details. So a data set of returns on a given set of assets can be segmented and then the variances can be compared for consistency. Following Lo and MacKinlay [33], we define $X_t = \ln(P_t)$ as the logarithm of price for asset i (with this subscript suppressed).

To make this more concrete, the reader should recognize that data sets can be segmented based on returns on assets across different periods of time and that no matter how the segmentation occurs, for a market to be efficient, the variances should be the same across each segment. For example, one-period returns, $X_t - X_{t-1}$, can be compared to two-period returns, $X_t - X_{t-2}$, and so on. Segmentation of the data can also involve cuts of asset returns based on other period returns, such as three-period returns and four-period returns. Examining four-period returns, for example, might yield four subsets, q, each with $n = 2500$ asset returns each, for $nq = 2500 \cdot 4 = 10{,}000$ total observations in the data set.

The unbiased maximum-likelihood estimators of the mean, μ, and variance, σ^2, of the transaction prices, based upon the observed returns in terms of the one-period difference of observed asset prices, $X_t - X_{t-1}$, are as follows for q segments of the data, each with n observations:

$$\hat{\mu} = \frac{1}{nq}\sum_{t=1}^{nq}(X_t - X_{t-1}) \tag{4}$$

and

$$\hat{\sigma}^2 = \frac{1}{nq-1}\sum_{t=1}^{nq}(X_t - X_{t-1} - \hat{\mu})^2. \tag{5}$$

In Eqs. (4) and (5), $\hat{\mu}$ and $\hat{\sigma}^2$ are estimates of the mean, μ, and variance, σ^2, with a sample composed of q subsamples with n observations each seen in the adjustments $1/nq$ and $1/(nq - 1)$. The denominator of the right-hand side of the expression for the variance reflects an adjustment for $q > 1$ segments.

To describe the intuition behind their use, we employ the arguments of Cochrane [10], who used variance ratios to examine random walks for GDP. Imagine that prices follow a pure random walk, as shown in Eq. (1) above. Cochrane showed that a random walk then can be expressed in terms of the number of time-differenced segments into which the data are split. If the asset's returns do not exhibit a trend because there is no reversion to the mean, then the variance of its returns will approach a constant, $2\sigma^2$, which is twice the conditional variance of the series. *Reversion to the mean*, in this context, implies that the serial correlation of the returns becomes more negative as the holding period of the asset lengthens (up to some point) [10]. This reversion to the mean, which is a stationary series per Dickey and Fuller [16], is indicative of an *inefficient market*. An *efficient market* occurs when the expected return is the previous period's return, which Dickey and Fuller note is a non-stationary series.

If the asset prices, X_t, revert toward a mean value, then X_t will be trend-stationary, and the trend line for the series should decline toward zero. Lo and MacKinlay [32] describe a technique for a maximum-likelihood unbiased estimation of $\mathrm{var}(X_t - X_{t-1})$ that allows for overlapping time differences of X_t when the variance $\hat{\sigma}_q^2$ is estimated. The idea of *overlapping time differences* comes with the differences in asset prices between period t and $t-2$, $t-1$ and $t-3$, and $t-2$ and $t-4$, etc., as opposed to with *sequential time differences*, t and $t-1$, and then between $t-1$ and $t-2$, for example. This allows for an entire range of values in a data set to be used, maximizing the use of the available information. It also permits the analyst to evaluate the use of $nq-q+1$ observations, rather than fewer observations, as would be the case if no overlaps were allowed. This gives rise to an *estimated subsample variance*:

$$\hat{\sigma}_q^2 = \frac{1}{m}\sum_{t=q}^{nq}\left(X_t - X_{t-q} - q\hat{\mu}\right)^2 \qquad (6)$$

where

$$m = q(nq - q + 1)\left(1 - \frac{1}{n}\right). \qquad (7)$$

Consistent with Lo and MacKinlay [32], we define the *variance ratio* as:

$$V_q = \frac{\hat{\sigma}_q^2}{\hat{\sigma}^2} \qquad (8)$$

We relied on Lo and MacKinlay for their derivation of the variance ratio. The interested reader should examine their work for the logic and additional details of derivation of the variance ratio as a means to test market efficiency. If a market is efficient for the q subsets of the data that are examined, then it should be that $V_q \cong 1$. This indicates that the variance of the returns remains relatively constant throughout all time periods q that are considered. If V_q is significant and different than 1, then the variance of the returns is not consistent over time, and this provides some evidence of inefficiency in the market. When V_q approaches zero, this is indicative of reversion to the mean. This might imply that there is a mean price and that markets which overprice an asset will tend to correct in the next cycle. On the other hand, when V_q is significant and greater than one in the presence of positive first-order autocorrelation (e.g., with the continuation of a trend), indicates that good returns on an investment in one period are indicative of continuing good investment returns in the future.

Lo and MacKinlay [32] suggest a statistic, z_q*, to test for market efficiency in the presence of heteroskedastic error terms:

$$z_q^* = \frac{\left(V_q - 1\right)\sqrt{nq}}{\sqrt{\theta_q}}, \quad z_q^* \sim N(0,1). \tag{9}$$

The null hypothesis, H_0, is that there is a random walk in asset price changes, indicating market efficiency and no opportunities for achieving abnormal returns. Under the null hypothesis, then, the z_q* statistic should have a zero mean. A non-zero mean, in contrast, will be an indicator of the absence of a random walk in this environment, as well as an indicator of the presence of market inefficiency. We detected heteroskedasticity in our data, which is not surprising. Lo and MacKinlay [33] introduced a homoskedastic error term, $z(k)$, to cover the case where heteroskedasticity cannot be detected. The authors point out that returns on most assets, including stocks, usually show some degree of heteroskedasticity. We determined that tests which assume homoskedasticity are not appropriate for this research. The heteroskedasticity-consistent estimators are:

$$\hat{\theta}_q = \sum_{l=1}^{q-1} \left[\frac{2(q-l)}{q}\right]^2 \hat{\delta}(l) \tag{10}$$

and

$$\partial(l) = \frac{nq \sum_{t=l+1}^{nq} (X_t - X_{t-1} - \hat{\mu})^2 (X_{t-l} - X_{t-l-1} - \hat{\mu})^2}{\left[\sum_{t=1}^{nq} (X_t - X_{t-1} - \hat{\mu})^2\right]^2}. \tag{11}$$

3.3. Appropriateness and challenges of efficiency analysis for online auction market returns

We next will justify the use of unit root and variance ratio tests that are developed in financial economics for application to the online auctions. There are crucial differences between the stock market and the online auction market. We address these differences by looking at how they affect our financial analysis, and discussing the contrasting econometric techniques can be used to handle these differences.

3.3.1. Information and ability

Professional investors who invest in the stock market are well informed, and equipped with the necessary training to be effective market traders. The same probably cannot be said for participants in the online auction markets. They should be viewed as hobbyists for the most part. Nevertheless, there are many professional traders among them. They act as professional dealers who often operate real-world collectible coin and stamp shops. Few of them know about valuation techniques involving risk and return, or the application of net present value or portfolio management techniques to control risk.

Bodie et al. [7] point out that trained investors will take advantage of any inefficiencies *in* stock markets, making inefficiencies disappear by the time typical investors can profit from them. Thus, all stock investors do not need to be informed, but rather just a segment of the market needs to be informed in order for price-correcting transactions to be made so that markets approach efficiency. This may be different for the online auction markets, where a pair of uninformed bidders can raise the price of an item to a level that informed bidders are not willing to match.

3.3.2. Uniformity

It may be tempting to view financial products like stocks, as being uniform across the market while products in online auction markets, such as rare coins and stamps, might be heterogeneous in quality. However, stocks change not only from stock to stock, but also from day to day as well, so that even companies can change drastically in relatively short periods. Coin and stamps do not vary much and are uniform across investors and time, unlike stocks. Thus, they are more similar to commodities than stocks.

The only differences between coins and stamps occur in terms of four factors: year minted or printed; the denomination of the coin or stamp; whether there are special conditions that are noteworthy relative to value, such as mint marks or mounting hinges; and the overall condition. These factors are probably more easily discerned than that myriad of factors that can affect a stock price, and all of these factors are easily detectible through the kind of text-based pattern matching that we have implement in the data collection work in this research. Moreover, most collectors typically agree on the valuation of a collectible once these four criteria have been identified.

3.3.3. Regulation

Both stock markets and online auction markets have the potential for information asymmetry. “Insider traders” can use non-public information to profitably trade, taking advantage of uninformed investors, while online auction sellers can misrepresent the quality of the product that they are selling. However, though these markets have the potential for information asymmetry, both have introduced steps that limit the effect of information asymmetry. For the stock market, regulation exists that insist on accurate reporting of information for investors, and punish insider trading, so that traders are prohibited from profiting from insider information.

There are fewer regulations for online auction transactions than there are for stock markets, yet anti-fraud regulations apply to sales in online auctions, with the possibility of lawsuits and even criminal action if a product is misrepresented. In addition, online auction marketplaces, like eBay, implement reputation systems that can hurt an opportunistic seller's future sales. Reputation systems have the twofold effect of deterring seller opportunism and punishing fraudulent or opportunistic actions [14] and [15]. This tends to drive out sellers who profit from information asymmetries and reduces the chance that an online auction market devolves into a “market for lemons” [1].

3.3.4. Thin markets

Thin markets occur when certain assets trade infrequently in comparison to others. In some settings, trading of these assets may be insufficient to the extent that it is not possible to effectively support price discovery for them. In research involving stock returns, the *number of periods* between trades of an asset is often set to 1 (or $l = 1$). For thinly-traded assets though, this cannot always be done. It may be two or more periods between trades, so that the pattern of trading is spotty, and it is not always possible to obtain transaction data for asset prices period by period. Our research is focused on evaluating market efficiency for collectible items, and specifically those that are thinly-traded. Other researchers have previously examined the efficiency of the collectible art market, where trading occurs in a similar way and makes price discovery more difficult [6] and [41].

To address the impact of thin trading for the evaluation of market efficiency in a specific market, Dimson and Marsh [18] recommended making adjustments to account for infrequent trades. Although their method is typically used when analyzing risk-adjusted returns, the same intuition applies to the empirical unit root analysis that we will conduct for this research. A thinly-traded investment weighting approach can be derived from their weighting scheme recommended to reduce the impact of thinly-traded securities when using the unit root test for an asset via:

$$\beta_t = \mathrm{cov}\left(\frac{\Delta R_t}{\sqrt{d_t}}, \frac{R_{t-l}}{\sqrt{d_t}}\right) \Big/ \sigma^2\left(\frac{\Delta R_t}{\sqrt{d_t}}\right) + 1. \tag{12}$$

The variable *d* indicates the number of periods that have elapsed since the last trade of asset *i* up to time *t*. Without adjustment, thinly-traded investments have a corrupting effect on unit root regression analysis. A number of methods can be used to adjust for infrequent trading as well. For example, Bradfield [9] describes two categories. One category is referred to as *Cohen methods*, which use aggregation of lagged and leading regression coefficients [11], [17] and [45]. The second category is *trade-to-trade methods*, which weight transactions based on the number of periods since the last trade, especially Dimson and Marsh [18]. The Dimson–Marsh correction adjusts the weight of thinly-traded assets in the regression, and reducing the inflating effect that thinly-traded investments have on the value of β.

4. STUDY 1: ONLINE MARKET EFFICIENCY FOR COLLECTIBLE COINS

We now turn to a discussion and analysis of the first of two collectible markets: coins.

4.1. The collectible rare coin data

We employed a software agent to collect prices on coins that were transacted on eBay during various periods across the years 1999, 2000 and 2001, 2002 and 2005. The earlier years of data were collected between April 24 and September 10, 2002. The later 2005 data were obtained in 2006. Data collection agents only included auctions of individual coins. They excluded auctions that did not sell the items that were offered, auctions that ended with a buy-it-now option, and listings that contained multiple items.

Admissible coins in our data set required that they had to have transacted for US$10 or more. This helps to increase the probability that coin transactions were the product of more knowledgeable and committed collectors, as opposed to “newbies” who might only be willing to spend several dollars to try out trading in the online environment. Our customized software agent can discriminate among other aspects of the description of a coin to effectively identify the exact coin for sale. It also can tell whether the transaction item was not actually a coin, but some sort of coin-collecting related supplies or commemorative medals, etc. Table 1 shows some descriptive information about the data that we used for this study.

Table 1
Data collected for the empirical analysis of the efficiency of online coin markets.

Year	From	To	Number of auctions	Bidders	Sellers	Unique coins	Mean selling price	Average bids per auction
1999	5/1/99	6/9/99	2169	1769	484	415	$41.36	6.27
2000	1/2/00	2/1/00	1884	1871	492	348	$39.10	5.78
2001	3/24/01	4/24/01	3913	3721	808	693	$41.66	5.93
2002	4/24/02	8/28/02	35,174	14,215	2850	3341	$57.56	6.00
2005	10/12/05	1/15/06	13,857	11,024	2202	1390	$89.44	7.52

Note: Typically, eBay only keeps auctions online for about 90 days from the end-of-sale date, although auctions are often available for longer periods depending on comments and eBay's purging program. Thus, long periods of data collection require an agent to be run over longer periods. We ran our agent to collect data over several years, starting with the 1999 rare coin data set. Auction text does not contain any type of serial number or unique identifier for coins, and thus we identify denomination, year, mint marks, and grade using a customized text pattern matching. Our pattern-matching algorithm has been tested against actual coin and stamp collectors with 100% inter-rater reliability, so that no coin that was identified by the agent was classified incorrectly according to coin and stamp collectors.

4.2. Estimation issues

There are a number of issues that affect the validity of empirical tests of financial theories. One consideration is the extent to which the findings of an analysis of market efficiency may be susceptible to the presence of outliers and extreme points in the data. To reduce the possibility of corruption due to influential data points, we employed an outlier test recommended by Neter et al. [40]. This led to the removal of about 2% (actually 748 or 1.99%) of the observations out of the 37,584 total observations.

Unit root analysis relies heavily on regression results to test for a unit root, a coefficient of one on an autoregressive term in a regression. We employ *robust regression* instead of *ordinary least squares* (OLS) since robust regression is more resilient to violations of the classical OLS assumptions. Robust regression is resistant to influences of a small part of the data, so even a large subset of outlying data will not cause a large change in values of the estimators. A common approach to robust regression is *M-estimation*, introduced by Huber [27]. This method uses *maximum-likelihood estimation* (MLE) to minimize the effects of heteroskedasticity. Another form of robust regression described by Mosteller and Tukey [39] is called *bi-weight* (or *bi-square*) *estimation*. It adjusts for extreme residuals using an iterative approach that determines a threshold point for a constant in a function that has the capacity to place a zero weight on extreme values. Our techniques mitigate the effects of heteroskedasticity and extreme outliers, which are present in our data. The result is a regression technique that yields consistent estimators.

4.3. Results

Table 2 contains the results of the Dickey–Fuller unit root analysis, along with a column containing the *bidder-to-auction ratio*, which can be considered as a measure of liquidity.

Table 2
Impact of previous returns on current returns for the coin data.

Year	Bidder-to-auction ratio	Unit root test	Variance ratio (V) tests		
		β	$q=2$	$Q=3$	$q=4$
1999	0.82	0.749***	0.346***	0.368***	0.397***
2000	0.99	0.698***	0.422***	0.534***	0.401***
2001	0.95	0.835***	0.377***	0.507***	0.492***
2002	0.40	0.999***	0.403***	0.378***	0.381***
2005	0.80	0.871***	0.388***	0.372***	0.375***

Note: ***$p<.001$. Unit root tests to establish the parameter, β, use robust regression. We employ variance ratio tests that examine the sample in two ($q=2$), three ($q=3$) and four ($q=4$) subsets to examine how the variances changed across different groupings of the data. A $\beta \to 1.00$ in the unit root tests is indicative of an efficient market. A variance ratio, V, of 1.00 is indicative of an efficient market also.

Liquidity is defined as the ability to sell an asset rapidly, with minimal loss of value, anytime within market hours. Publicly-traded securities typically are considered to be more liquid than items sold in online auctions because of the immediacy with which publicly-traded securities trades are able to be made. Thus, liquidity is an important issue in online auctions also. Pratt [42] finds that market discounts on closely held firms whose stock is not publicly traded may exceed 30%. In online auctions, the more bidders there are, the more liquid the auctioned assets, since a high number of bidders allows sellers to sell items relatively quickly for good prices. As the number of bidders decreases or the number of auctions increases, online auction market liquidity decreases, and sellers face greater competition and fewer buyers for their goods, which drives prices down.

We weighted our results to reduce the effect of thin trading using the Dimson–Marsh method, so that the results that we have presented are robust. Our confidence in these results was strengthened based on our evaluation of the unweighted results, which showed a similar pattern. Similar patterns were also demonstrated by the results of tests with outliers removed and also with data omitted to facilitate the variance ratio analysis. The *t*-statistic is negative since the coefficient that we tested actually is $\beta - 1$ rather than simply β. Coefficient estimates of a value $\beta < 1$ will return negative *t*-statistics.

All of the years in Table 2 have unit root β values that are less than 1.0 and significant, although one, β_{2002}, is very close to 1. The series of β for all years can be interpreted as evidence of inefficiency resulting in *reversion to the mean*. Collectible coin auctions that offer abnormally low or high returns can be indicative of underpayment and overpayment by the final bidder. By contrast, in an efficient market defined by a random walk, β ought to be statistically no different from 1.0. Fig. 1a and b show how the persistence of abnormal returns varies with the bidder-to-auction ratio.

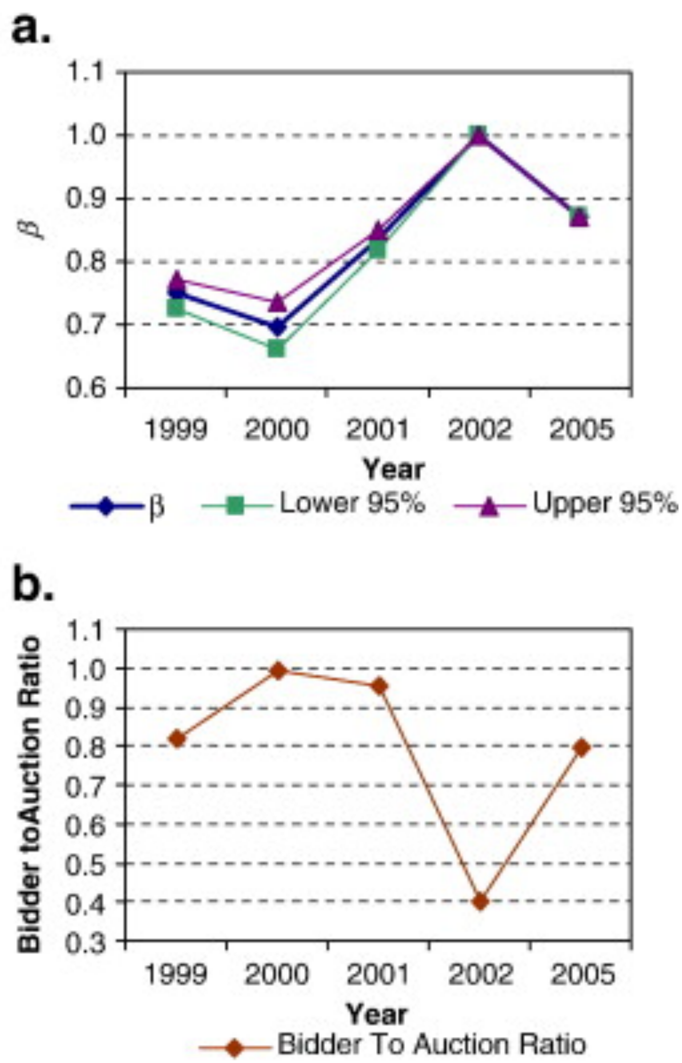

Fig. 1.
Test results for the coin data, 1999–2002, and 2005. Note: β = 1.0 means that the current return is as likely to increase or to decrease, indicating an efficient market. With estimated values of β < 1.0, however, our results suggest inefficiencies in the online coin market. a. Unit root test results. b. Bidder-to-auction ratio results.

As the number of bidders increases, the persistence of abnormal returns decreases, resulting in more temporary effects from abnormal returns. As the number of auctions increases, the persistence of abnormal returns appears to increase, indicating that abnormal returns tend to affect asset prices further into the future. When unanticipated price changes persist into future sale prices (i.e., β = 1.0), we can say that the market is *efficient*. Similarly, if prices changes do not persist into future sales, as is the case with this study (i.e., β < 1.0), this indicates the market is inefficient. Once we establish inefficiencies in a market, we then examine how long unanticipated price changes affect future price levels, if at all.

Fig. 1a and b show that the unit root test and bidder-to-auction ratio results have inverse patterns relative for the persistence of abnormal returns, as measured by β for the coin data. They nearly sketch mirror images of one another. When the bidder-to-auction ratios were closer to the 1.0 level in 1999, 2000, and 2001 (i.e., $\beta_{1999} = 0.749$, $\beta_{2000} = 0.698$, $\beta_{2001} = 0.835$), the likelihood that the market was efficient was lower due to the lower values of the unit root test parameters. These results hint that liquidity is inversely rated to efficiency and persistence in online auctions for coins. The relationship may be more complicated; it is possible that liquidity loss will scare away sellers, causing a reduction of the number of auctions, increasing efficiency and price change persistence in later periods. We do not find this here; it may take several years of continuous data collection to resolve this issue. A bidder-to-auction ratio near to 1.0 indicates that the number of bidders approaches the number of auctions. Because we aggregate at the year level, there are very few data points. However, even with a small sample size, we find a − 85.9% correlation between the bidder-to-auction ratio and β at the yearly level, with a p-value of about 0.02, making this inverse relationship statistically significant. This strengthens our observation of an inverse relationship between the bidder-to-auction ratio and the persistence of abnormal returns.

When the bidder-to-auction ratio fell to the 0.40 level in 2002, the estimated value of β from the unit root test approached very close to 1.0 ($\beta_{2002} = .999$), with a tight confidence interval of [0.9989, 0.9994]. In 2005, the persistence of abnormal returns as they relate to market efficiency, β_{2005}, appears to have fallen to roughly 0.87, as the bidder-to-auction ratio increased to 0.80. Though our sample size is large enough to detect relatively small effects, the estimated value of β_{2002} from the unit root analysis is so close to 1.0 that one could argue that there is no practical difference, even though there is a statistically significant difference. This is an interesting result. It permits us to preliminarily conclude that the online market for collectible coins approached efficiency in 2002. Malkiel [36] makes a similar argument with critics of efficiency in the stock market, by claiming that markets are so close to efficiency in these cases that profiting from inefficiencies won't even cover the listing charges. As can be seen in Fig. 1b, these rises and falls roughly correspond to increases and decreases in the bidder-to-auction ratio. This offers a strong implication that online auction markets can increase the persistence of abnormal returns if there are enough auctions compared to bidders. We contend that these results show that, regardless of the number of items for sale, the same number of bidders pursues the same number of goods looking for purchases. With more auctions to choose from, the persistence of abnormal returns appears to increase as bidders are able to better compare prices and participate in different auctions.

Cochrane [10] informs us that the variance ratios are indicative of the percentage of variability due to a random walk. The variance ratios in all of the tests that we conducted hovered around 41% ($V^{Average}$ = 0.409 to be exact, with $V^{Minimum}$ = 0.346 and $V^{Maximum}$ = 0.534). Thus, Table 2 suggests that about 59% of the total variance of returns cannot be explained by a random walk. This indicates that coin returns are trend-stationary and mean-reverting over this time period, and have relatively little permanent random walk component. Thus, using both unit root tests and variance ratio tests gives us an indication that coin asset prices do regress toward a mean, but that the prices are mean-reverting at different rates. They revert more slowly as the number of bidders increases or the number of auctions decreases.

5. STUDY 2: ONLINE MARKET EFFICIENCY FOR COLLECTIBLE STAMPS

We now look at market efficiency and the persistence of abnormal returns over time for stamps.

5.1. The collectible stamp data

We obtained stamp price data for this study from individual stamp auction sites on eBay (via stamps.ebay.com) with the use of software agents to support data collection. The agents targeted auctions of U.S. stamps in mint or unused condition, issued in or before 1940, with data gathered between April 6, 2007 and October 6, 2007. The agents obtained prices, the condition of the stamp for sale and the characteristics of buyers and sellers. Item text was analyzed to determine standard quality measures for each stamp. (For stamp quality terms, see www.glassinesurfer.com/stamp_collecting/gsgrading.shtml.) Typical stamp industry standard quality measures include whether the stamp has been used, if the gum has been damaged by hinging, how good the color quality is, and whether there are problems with the centering of the image in the stamp. As with coins, there are also technical terms used to describe a stamp's condition, such as “fine,” “very fine,” “fine-very fine,” and “mint.” Items that did not sell, auctions with the exercise of a buy-it-now option, and listings containing multiple items were excluded.

We gave much consideration to the refinement of the search criteria that determined the data we collected. Stamps come in a variety of formats, including cancelled and unused, rectangular panes and numbered plate blocks, coils, and first-day-of-issue covers. The issues also vary from regular post to air mail, to government mail and parcel post, and tax stamps. To limit the scope of our data collection, we focused on auctions for single unused stamps. We excluded selling multiple stamps (e.g., a roll of stamps), stamp equipment (e.g., mounting hinges for placement in a book), or reproductions. We also eliminated auctions where the exact stamp could not be identified by the description (e.g., “1977 Stamp for Sale”) or where the condition of the stamp was suspect (e.g., “extra fine, but damaged,” “mint with hole,” etc.). Our filtering effort was intended to ensure that stamps were being compared to like stamps. About one out of forty auctions whose data we gathered did not fit our criteria, and we excluded them from analysis as a result.

Our data can be categorized into two different sub-markets of stamps. Many stamp collectors concentrate, on only one of these sub-markets. Table 3 describes the data that we collected in terms of the different stamp categories. It was not feasible to divide the stamp data by time as we did with the coin data. There would likely be an overlap in the bidders who were following and bidding on the stamps. This would lead to issues in using the number of bidders as a proxy for market participants. The overlaps were always less than 25% of the total number of bidders, which was acceptable to us, although no overlaps – such as in the coin data – would have been better.

Table 3
Data collected for the empirical study of the efficiency of the online stamp market.

Category	Number of auctions	Bidders	Sellers
1800–1900	2971	1035	487
1900–1940	5567	1796	623
Totals	8538	2831	1110

Note: Data from April 4, 2007 to October 4, 2007. They are continuous in time, with the exception of seven days of data lost during June 2007, when the computer running the agents was moved to a data center. Another two days of data were lost due to technical issues. The original data had two additional categories, including Air Mail with 202 auctions and 94 bidders, and Alaska Yukon with 78 auctions and 68 bidders, respectively. These auctions were removed from our study because we have reason to believe that there were many more bidders, perhaps thousands, who were reviewing these stamp auctions concurrently with stamp auctions in the 1800 and 1900 categories. With such a low number of auctions in a sub-market where the overall market has thousands more auctions, the number of bidders that we could identify may not represent the actual count of bidders that were reviewing the market. As a result, we caution other researchers to make sure that they have enough market liquidity before they try to perform this kind of analysis.

5.2. Estimation issues

Analysis of our stamp data required many of the same controls that were required by the coin data set, only based on the different descriptors that are used to identify the quality of stamps. These include conditions grades (e.g., mint, fine and very fine), and other specialized marks or conditions (e.g., never hinged). Our approach regarding the elimination of outliers involved identifying and omitting observations for which ln(*Price*) was outside a band bounded by three standard deviations of the mean (i.e., the 99th percentile band). This excluded less than 1% of the data. The logarithms of the stamp price change data were skewed right, and violated the normality distribution assumptions associated with OLS regression. Thus, we employed the same robust bi-weight and M-estimation methods as we did for the collectible coins.

In addition to the typical econometric issues that we described earlier for coins, and for which we made the appropriate tests and adjustments, one of the primary challenges in working with data of the sort that are involved in analyzing online stamp market efficiency has to do with the manner in which we determine what comparisons are to be made for prices. It is critical to understand what is possible in terms of comparing a current transaction price to a prior transaction price of a stamp, as a basis for identifying price movement. In our data set of stamps, it was possible to observe stamps that traded irregularly (as you might expect for markets with thinly-traded assets), sometimes with several days or weeks between trades of an individual stamp. As a result, to support effective coding, we found that it was appropriate to apply an approach that was used by Dimson and Marsh [18], involving weighted measures for the asset returns based on the number of days since the time when the previous trade occurred.

Another estimation issue was determining the number of price observations to be included to assess price changes via the unit root and the variance ratio analyses. Recognizing the limitations of using a small amount of data for the price series versus using a small number of auctions, our research design involved a trade-off. This trade-off was between including stamps that had enough observations in their price change time-series relative to including enough bidders and auctions, so as to be representative of the actual trading that was occurring in the market. We determined that it was feasible to use stamps with fifteen price observations to obtain as few as fourteen price change data points, which still yielded a large enough number of bidders and auctions so our analytical approach was viable.

5.3. Results

Table 4 shows empirical results from an examination of the stamp sub-markets for 1800 to 1899 and 1900 to 1940, along with unit root test and variance ratio results on the price change series. The bidder-to-auction ratio for stamps from 1800 to 1899 is 0.35, and for stamps from 1900 to 1940 is 0.32. Although there are some notable differences, the results of the stamp data are similar to the results of the coin data at a high level of inspection. Both data sets were collected from eBay collectors' markets.

Table 4
Impact of prior returns on current returns for the stamp data, 1800s and 1900s stamps.

Century	Bidder-to-auction ratio	Unit root test	Variance ratio (V) tests		
		β	$Q=2$	$q=3$	$Q=4$
1800–1899	0.35	0.901***	0.428***	0.347***	0.325***
1900–1940	0.32	0.898***	0.418***	0.355***	0.330***

Note: All price change series used in this analysis include no fewer than 15 price change observations. We felt that this was appropriate because the stamp data exhibits thinner trading than the coin data. The coin data had no fewer than 25 price change observations. Using no fewer than 15 stamp price observations helped us to preserve the number of data points that were used to establish the β and V values above. In addition, this choice had no critical impact on the variance ratios that we estimated. We used unit root tests to establish the unit root test parameters, β, via robust regression. We employed variance ratio tests on the sample in two ($q=2$), three ($q=3$) and four ($q=4$) subsets to examine how the variances changed across the groupings of the data. Signif.: ***$p<.001$.

All of the unit root β values are less than one and significant ($\beta_{1800\text{–}1899} = 0.901$, $p < 0.001$; $\beta_{1900\text{–}1940} = 0.898$, $p < 0.001$). This suggests that the online auction stamp market is not efficient, and that prices eventually trend toward a mean. However, abnormal returns in this market show a high level of persistence and tend to revert slowly back to a mean. We are examining daily returns, so even values close to 1 but with a significant difference will still revert to a mean. We consider these not to be efficient. For example, a 90% persistence of abnormal returns indicates that after 30 days only 4.24% (= $.90^{30}$) of the abnormal returns will still be reflected in the price of the item. This further indicates that previous abnormally high or low returns are reflected in the market for some time before the effects finally disappear. We also conducted sensitivity analysis for the unit root coefficients and variance ratios in relation to the minimum number of price change observations required inclusion in the study. A time-series of fifteen price changes was required. We tested data sets with as few as ten and as many as twenty price changes in a group. In each case, the unit roots and the variance ratios were significantly different from one.

The variance ratios averaged about 0.37 ($V^{Average} = 0.367$, $V^{Minimum} = 0.325$ and $V^{Maximum} = 0.428$). This suggests that just over 60% of the variation cannot be explained by a random walk. Thus, as with the coin data, the stamp data appear to be trend-stationary and mean-reverting, at least over the time period that we observed the prices of these stamps. The variance ratios are similar for both sub-markets (i.e., $V_{q=2}$: 0.418; $V_{q=3}$: 0.355; and $V_{q=4}$: 0.330 for the 1900–1940 stamps versus $V_{q=2}$: 0.428; $V_{q=3}$: 0.347; and $V_{q=4}$: 0.325 for the 1800–1899 stamps). Though the differences in these variance ratios are not large, the results suggest that the amount of variability accounted for by the random walk may be associated with an increase in market liquidity as indicated by a decrease in the bidder-to-auction ratio.

The 1800 to 1899 stamp sub-market, with 2971 auctions, is roughly half the thickness of the 1900 to 1940 stamp sub-market, with 5567 auctions in this study. We note that the market thickness, in and of itself, has little effect on the variance associated with a random walk. Although the market appears to be inefficient in that stamp prices tend to revert to the mean, the abnormal returns we observed show a great deal of persistence, approaching 0.9, with 1.0 being perfect persistence. Our results are interesting in that the economic literature on the thickness of markets does not seem to apply too well to the online auctions in this study. However, the inefficiencies we have observed suggest that even though technology has improved these thin markets, it still has not completely eliminated inefficiencies in online auctions.

6. DISCUSSION

Online auctions have created market liquidity and made available auction-like market mechanisms in settings where traditional auctions often have catered to a very select and small number of participants. Now online auctions reach millions of participants, with thousands of potential bidders for each auction. As market depth and liquidity increase in online auctions, researchers should view investments in collectibles through the lens of financial economics. We assessed coin and stamp markets for efficiency, using methods similar to those used to measure efficiency of the stock markets. We applied two different methods of measuring random walks to our data. Our exploration of market efficiency here points to similarities and differences between the markets. Through this process, we are able to point out new findings that contribute to our understanding about the potential for speculation in online auctions of collectibles.

Cochrane [10] shows that, for a market to be efficient and contain a random walk, the variance needs to be consistent throughout the market. The variance ratio ought to be approximately equal to 1.0 in an efficient market. We performed variance ratio analysis in the two markets. The variance ratios of the coin sub-markets that we studied range from 0.346 to 0.534. The results were similar to the two stamp sub-markets, where the variance ratios form a tighter range from 0.325 to 0.428. We observed that in both coin and stamp markets the variability that is *not* explained by random walks hovers around 60%. This result is interesting; these markets contain similar variability of the effects of random walks in conjunction with different degrees of market liquidity. The conventional wisdom suggests greater market depth results in a tendency toward efficiency, yet we found that this is not necessarily so with our online auction data. Market depth had little effect on efficiency in online auctions, but market liquidity measured by the ratio of buyers to auctions seems to have an inverse relationship on persistence of abnormal returns in the collectible markets, approaching an efficient market as the number of bidders decreases.

Second, using unit root analysis, both our sub-markets showed a significant difference in persistence of abnormal returns that appears to have a relationship with the bidder-to-auction ratio. We find that the number of bidders in relation to the number of auctions seems to be correlated with the persistence of abnormal returns, based on period-to-period price changes, in online auction collectible markets. Markets with a lower number of bidders per auction showed more persistence of abnormal returns than markets with a high number of bidders per auction. The persistence of abnormal returns in both the collectible coin and stamp markets approaches 1.0 as the bidder-to-auction ratio drops to around 40%. The increase in persistence of abnormal returns is due to increased in bidder competition. When there are more bidders vying for the same item, the persistence of the abnormal returns declines. Thus, if bidder competition increases and there are more bidders competing for fewer auctions, then an individual bidder will have a greater chance to have a larger impact on price. This is in strong contrast to a less competitive environment, where bidders can choose the auctions in which they wish to participate with greater ease. This will tend to stabilize returns and allow abnormal returns to persist into the future.

7. CONCLUSION

This research examines the efficiency of Internet auctions from a financial economics point of view. We analyzed online auction markets for stamps and coins to gauge efficiency, and the possible explanations consistent with the observed empirical regularities.

7.1. Contributions

Our research points out that that there are differences between the stock market and the online auction market, including the inability to sell short in the online auction market and the ability of two investors to easily influence the price of items in online auction markets. These differences can lead to inefficiencies so that the prices of assets sold in online auction markets do not reflect all information available to traders and investors in that market. An alert investor can make excessive profits when investing in assets in an inefficient market when compared to investments made in an efficient market. Our research shows that the online auctions that we studied are not altogether efficient, but that they approach efficiency as the number of bidders decreases in relation to the number of auctions. Our major contribution is to document their presence and show how inefficiencies in the collectible online auction markets may arise. A related contribution is to show that these inefficiencies can be diminished as the number of auctions increases with respect to the number of bidders. Moreover, we point out that it is feasible and beneficial in the long run that an inefficient online auction market will attract sellers who can profit from these inefficiencies to the point where the market approaches efficiency.

We find that the persistence of abnormal returns required for an efficient market may ensue as the number of bidders decreases in relation to the number of auctions. This is due, we argue, to online auction bidders' ability to examine prices in concurrent and past auctions to determine a proper bid level, and to observe the lower level of bidder competition, consistent with lower levels of the bidder-to-auction ratio. Since eBay's auction mechanism mimics a second-price sealed-bid auction, it is impossible for a single uninformed bidder to be a price-maker. However, two bidders acting in concert can affect a price. As the number of bidders decreases or bidders begin to have more auctions to search and select (or both), it will be harder to find two uniformed bidders who are bidding on the same item.

We have discussed the similarities and differences between the rare coin and rare stamp collectible online markets at length in this article. We established somewhat different results for collectible stamp auctions than we did for the coin markets, although the main features of the results were retained. We found evidence of persistent returns rather than full market efficiency with more thinly-traded stamps, and similar degrees of variance in returns tied to the apparent random walk component of returns.

For the collectible coin markets that we analyzed in different time periods spanning seven years, we detected an inverse relationship between the persistence of abnormal returns and the bidder-to-auction ratio. We also revealed inefficiencies in the collectible markets where a speculator might have an opportunity to take advantage of abnormally low sale prices for stamps or coins and resell them for abnormally high prices. Our variance ratio tests show that these inefficiencies are relatively consistent, despite some differences in market liquidity over the years. The collectible stamp markets that we analyzed showed similar and relatively high levels of persistence of abnormal returns, coupled with relatively low bidder-to-auction ratios, as is consistent with what we find in the rare coin market. Our unit root tests suggested that abnormal returns of prior auctions tend to fade, as the returns revert to their mean levels.

Our research also delivers a number of contributions that offer surprise value and interesting new knowledge for academic research in IS, finance, and e-commerce, and for the managerial practices involved in the development of online auction markets. One contribution that we offer is to demonstrate the use of empirical evaluation techniques that provide evidence about whether online auction markets for collectible coins and stamps are efficient. We also measured the persistence of abnormal returns that may occur in these online markets. Our empirical analysis shows the interplay between the results of random walk tests, based on both unit root tests and variance ratio tests, for market efficiency and the persistence of abnormal returns. We examined the bidder-to-auction ratio to show contrasts between what happens to our estimates with respect to the unit roots for persistence of abnormal returns. We also applied a variance ratio analysis approach to gauge the extent to which the movement of coin and stamp asset prices and returns in online auctions are comprised of a random walk component. We also used unit root tests and variance ratio tests to show the extent to which there is reversion to a mean value as a result of market inefficiency. Finally, we illustrated the use of different approaches to the segmentation of our data to test market efficiency across different numbers of periods (and numbers of transactions, in the case of thinner asset trading), as well as across different asset categories.

7.2. Limitations and future research

We learned that the bidder-to-auction ratio is important in determining the level of persistence in abnormal returns in online auctions, and that market liquidity has little effect on the persistence of abnormal returns and on the amount of variance explained by random walks. Our insights are consistent with various stock market phenomena that have been observed by others, such as bubbles, but we nevertheless caution readers to limit their interpretation of our results to online auctions.

It is appropriate to point out to the reader that there is typically a great deal of measurement noise that goes along with the evaluation of online auction performance. Our research should not be viewed as an exception to this rule. Future research has the potential to provide a clearer picture of the effects of the bidder-to-auction ratio, especially in an even larger data set for the stamp market, so that we can ensure that there are no overlaps in the population of bidders across the different asset categories. In addition, we intentionally dropped certain sub-markets for collectible stamps that exhibited too thin trading in the time frame of our study. We were not confident that the number of bidders who observed the market was accurately reflected when only a small sample of auctions is retrieved. Clearly, data from thicker markets are appropriate before such analysis should be attempted. Indeed, there needs to be thousands of observations, before it is possible to effectively examine a market to determine its efficiency, the persistence of abnormal returns after different kinds of shocks occur, and the effects of the bidder-to-auction ratio.

We only investigated two markets over a limited period of time. Our findings may not generalize to other auction markets. Nevertheless, the methodological approach that we have demonstrated should be helpful as a basis for effective exploration of different online market contexts. Other researchers will benefit from thinking through some new ways to refine our techniques to make them more effective. Readers can take away other implications too. Sellers naturally want to operate in markets that provide depth, market liquidity, participation, and offer appropriate sale prices. They appreciate how online auction markets support effective price discovery. Yet they are likely to gravitate toward markets with higher levels of participation, since the presence of many bidders and auctions creates a basis for inefficiencies and thus the chance that they can sell their items at an increased price. Speculators may appreciate inefficiencies – both as buyers and sellers – and may wish to participate in online auctions with many buyers, but fewer competing auctions, in an effort to profit from the available inefficiencies.

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REFERENCES

[1] G.A. Akerlof, The market for lemons: quality uncertainty and the market mechanism, Quarterly Journal of Eeconomics 84 (3) (1970).

[2] S. Alexander, Price movements in speculative markets: trends or random walks? Industrial Management Review 2 (2) (1961).

[3] R. Ariel, High stock returns before holidays: existence and evidence on possible causes, Journal of Finance 45 (5) (1990).

[4] O. Ashenfelter, K. Graddy, Auctions and the price of art, Journal of Economic Literature 41 (3) (2003).

[5] P. Bajari, A. Hortaçsu, The winner's curse, reserve prices and endogenous entry: empirical insights from ebay auctions, Rand Journal of Economics 34 (2) (2003).

[6] W.J. Baumol, Unnatural value: or art investment as floating crap game, American Economic Review 76 (2) (1986).

[7] Z. Bodie, A. Kane, A. Markus, Investments, Irwin, Boston, MA, 1993.

[8] J. Boudoukh, M.P. Richardson, R.F. Whitelaw, A tale of three schools: insights on autocorrelations of short-horizon stock returns, Reviewof Financial Studies 7 (3) (1994).

[9] D. Bradfield, Investment basics XLVI: on estimating the beta coefficient, Investment Analysts Journal 57 (2003).

[10] J.H. Cochrane, How big is the random walk in GNP? Journal of Political Economy 96 (5) (1988).

[11] K. Cohen, G.A. Hawawini, S.F. Maier, R.R. Schwartz, D.D. Whitcomb, Friction in the trading process and the estimation of systematic risk, Journal of Financial Economics 12 (2) (1983).

[12] P.A. Cootner, Stock prices: random vs. systematic changes, Industrial Management Review 3 (2) (1962).

[13] A. Damodaran, Investment Valuation, 2nd edition, John Wiley and Sons, New York, NY, 2002.

[14] C. Dellarocas, The digitization of word-of-mouth: promise and challenges of online feedback mechanisms, Management Science 49 (10) (2003).

[15] C. Dellarocas, C.A. Wood, The sound of silence in online feedback: estimating trading risks in the presence of reporting bias, Management Science 54 (3) (2008).

[16] D. Dickey, W.A. Fuller, Distribution of the estimates for autoregressive time series with a unit root, Journal of the American Statistical Association 74 (366) (1979).

[17] E. Dimson, Risk measurement when shares are subject to infrequent trading, Journal of Financial Economics 7 (2) (1979).

[18] E. Dimson, P.R. Marsh, The stability of UK risk measures and the problem of thin trading, Journal of Finance 38 (3) (1983).

[19] R.F. Easley, C.A. Wood, S. Barkataki, Bidder strategies and the winner's curse: an empirical investigation,Working Paper,Notre Dame University, South Bend, IN, 2007.

[20] E.F. Fama, Efficient capital markets: a review of theory and empirical work, Journal of Finance 25 (2) (1970).

[21] E.F. Fama, K.R. French, Permanent and temporary components of stock prices, Journal of Political Economy 96 (2) (1988).

[22] K.R. French, Stock returns and the weekend effect, Journal of Financial Economics 8 (1) (1980).

[23] K.D. Garbade, W.L. Silber, Technology, communication and the performance of financial markets: 1840–1975, Journal of Finance 33 (3) (1978).

[24] S.J. Grossman, J.E. Stiglitz, On the impossibility of informationally efficient markets, American Economic Review 70 (3) (1980).

[25] R. Haugen, J. Lakonishok, The Incredible January Effect, Dow Jones Irwin, Homewood, IL, 1988.

[26] H.S. Houthakker, Systematic and random elements in short-term price movements, American Economic Review 51 (2) (1961).

[27] P.J. Huber, Robust estimation of a location parameter, Annals of Mathematical Statistics 35 (1) (1964).

[28] D. Keim, Size-related anomalies and stock return seasonality: further empirical evidence, Journal of Financial Economics 12 (12) (1983).

[29] A.B. Larson, Measurement of a random process in future prices, Food Research Institute Studies 1 (3) (1960).

[30] S.F. Leroy, Risk aversion and the martingale property of stock returns, International Economic Review 14 (2) (1973).

[31] S.F. LeRoy, Efficient capital markets and martingales, Journal of Economic Literature 27 (4) (1989).

[32] A.W. Lo, A.C. MacKinlay, Stock market prices do not follow random walks: evidence from a simple specification test, Review of Financial Studies 1 (1) (1988).

[33] A.W. Lo, A.C. MacKinlay, A Non-Random Walk Down Wall Street, Princeton University Press, NJ, 1999.

[34] R.E. Lucas, Asset prices in an exchange economy, Econometrica 46 (6) (1978).

[35] B.G.Malkiel,ARandomWalkDownWall Street,1st edition,Norton,NewYork,NY,1973.

[36] B.G. Malkiel, The efficient market hypothesis and its critics, Journal of Economic Perspectives 17 (1) (2003).

[37] J. Mei, M. Moses, Art as an investment and the underperformance of masterpieces, American Economic Review 92 (5) (2002).

[38] H. Mendelson, Consolidation, fragmentation and market performance, Journal of Financial and Quantitative Analysis 22 (2) (1987).

[39] F. Mosteller, J.W. Tukey, Data Analysis and Regression: A Second Course in Statistics, Addison-Wesley, New York, NY, 1977.

[40] J. Neter, M.H. Kutner, C.J. Nachtsheim, W. Wasserman, Applied Linear Statistical Models, 4th edition, Irwin, Chicago, IL, 1996.

[41] J.E. Pesando, Art as an investment: the market for modern prints, American Economic Review 83 (5) (1993).

[42] S.P. Pratt, Valuing a Business: The Analysis of Closely Held Companies, 2nd edition, Dow Jones Irwin, Chicago, IL, 1989.

[43] J.G.Riley,W.F. Samuelson,Optimal auctions,American Economic Review71 (3) (1981).

[44] P. Samuelson, Proof that properly anticipated prices fluctuate randomly, Industrial Management Review 6 (2) (1965).

[45] M. Scholes, J. Williams, Estimating betas from nonsynchronous data, Journal of Financial Economics 5 (3) (1977).

[46] P.S. Schreiber, R.F. Schwartz, Price discovery in security markets, Journal of Portfolio Management 12 (4) (1986).

[47] A. Swiatek, Coin World Guide to U.S. Coins: Prices and Value Trends, Amos Hobby Publishing, New York, NY, 2001.

[48] R. Thaler, The Winner's Curse: Paradoxes and Anomalies of Economic Life, Princeton University Press, NJ, 1992.

[49] R. Vragov, C2C internet auctions and neoclassical economics: preliminary experimental findings, Working Paper, Baruch College, City University of New York, New York, NY, 2005.

[50] C.A. Wood, Risk and return in online coin auctions over a short horizon, Proceedings of the International Conference on Information Systems, Paris, France, December 14–17, 2008.