Risk, return, and sentiment in a virtual financial market†

Maurizio Montone\textsuperscript{a}, Remco C. J. Zwinkels\textsuperscript{b,c,*}

\textsuperscript{a}Utrecht University
\textsuperscript{b}Vrije Universiteit (VU) Amsterdam
\textsuperscript{c}Tinbergen Institute

Abstract

The joint hypothesis problem casts doubt on the results of market efficiency research. To address this issue, we study price formation in a large virtual asset market where fundamentals are fixed, predetermined, and publicly known. In this market, we find that a number of well-established determinants of returns, such as factor-mimicking portfolios or investor sentiment, represent genuine mispricing rather than risk. The magnitude of the results suggests that prices in real financial markets include a substantial behavioral component, which is likely underestimated in canonical asset pricing tests.

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1. Introduction

One key issue in modern asset pricing is to distinguish changes in fundamentals from mere biases in investor behavior. To identify the former, research has proposed a number of factor models. The idea is to construct portfolios that capture (or “mimic”) sources of common variation of returns that are otherwise latent, such as a distress factor (see, e.g., Fama and French, 2004). Notable examples are portfolios of stocks ranked on size or book-to-market (Fama and French, 1992), or momentum (Carhart, 1997), among many others. It is unclear, however, whether such factors represent genuine risk, or also mispricing (see, e.g., Daniel and Titman, 1997; Stambaugh, Yu, and Yuan, 2012).

A different approach is to try and identify investor biases directly, through a proxy called “sentiment”. The idea is to capture instances in which economic agents hold unduly optimistic or pessimistic beliefs, i.e., not based on the facts at hand (Baker and Wurgler, 2006). This process typically involves the creation of an index. The most prominent examples in sense are the indices of consumer sentiment (Carroll, Fuhrer, and Wilcox, 1994), and investor sentiment (Baker and Wurgler, 2006, 2007; Baker, Wurgler, and Yuan, 2012).

*Corresponding author. Address: Vrije Universiteit Amsterdam, De Boelelaan 1105, Amsterdam, 1081 HV, Netherlands. Email: r.zwinkels@vu.nl, Tel: +31 20 59 85220.
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Nonetheless, the issue with these measures is that they may still reflect economic fundamentals to some extent (see, e.g., DeVault, Sias, and Starks (2019) for an excellent discussion).

Both strands of literature are then subject to the well-known joint hypothesis problem (Fama, 1970), as they rely on assumptions that are not easily verifiable. In this paper, we propose a solution to identify a credible and ex-ante distinction between fundamentals and investor behavior, and quantify the relative impact of the two on asset returns. We consider a large virtual asset market in which fundamentals are fixed, predetermined, and publicly known, which allows us to directly assess the impact of investor behavior on price formation independently of economic fundamentals. As such, this is a unique setting to carry out asset pricing tests.

We find two main empirical results. First, a number of factors that are known to price returns, such as size and book-to-market, represent mispricing rather than risk. Second, sentiment has an independent and substantial impact on asset prices. The results suggest that prices in real-life financial markets include a substantial behavioral component, which we estimate to account for about one third of the overall asset volatility. Interestingly, the magnitude of this effect is close to that of the decrease in returns on asset pricing anomalies that follow academic publications (McLean and Pontiff, 2016).

Experimental studies also offer a solution to the joint hypothesis problem, by recreating a simplified asset market in which fundamentals are predetermined and publicly known. The main finding of this line of research is that prices deviate from fundamentals, but eventually reach the rational equilibrium. However, the structure of such markets features a small number of assets (typically one or two), participants (up to a few dozen), and trading sessions (30-60 max). As a result, this setup is not suitable for portfolio analysis, which limits the potential to study asset pricing anomalies. Also, sentiment can only be defined endogenously.

On the other hand, betting markets also offer the opportunity to study market efficiency (Sauer, 1998). With respect to experimental markets, this setting features a large number of assets and participants. However, fundamentals are privately known (if at all), assets have a short time span (for example, a sports week), and transactions are zero-sum games (unlike stocks). These features make it hard to study standard asset pricing anomalies, and also make the definition of sentiment rather narrow if compared to that of other financial markets.

In our study, we overcome these limitations. We analyze the price formation process from an in-play market for soccer players in the online video game FIFA 19, which shows many similarities in structure and demographics to real-life financial markets. In addition, it is a closed system in which the economic fundamentals are captured by a set of “ratings”, i.e., predetermined scores for a number of player characteristics. These ratings are known to all participants, fixed, defined prior to the start of the market, and orthogonal

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1See Forsythe, Palfrey, and Plott (1982, 1984), and Friedman, Harrison, and Salmon (1984), for relatively short-lived assets, and Smith, Suchanek, and Williams (1988) for relatively long-lived assets.

2For example, bettors tend to exhibit a preference for underdogs (Ali, 1977; Snyder, 1978; Asch, Malkiel, and Quandt, 1982; Asch and Quandt, 1987; Ziemba and Hausch, 1987; Golec and Tamarkin, 1991; Dier, 2011), or for specific teams (Avery and Chevalier, 1999; Kuypers, 2009; Levitt, 2004; Forrest and Simmons, 2008).
to the physical world. To the best of our knowledge, this paper is the first to study the price dynamics of a video game’s in-play market.

FIFA is a soccer simulator video game, and one of the most popular games worldwide. FIFA 19, the version of the video game we study, was sold approximately 20 million times and played by 36 million gamers. It is especially popular in Central and South America, Eastern and Southern Europe, and the Middle East. Whereas there are more sports-simulator video-games available, also with player markets, FIFA is by far the most popular. We specifically focus on the game mode FIFA Ultimate Team (FUT), which allows gamers to play against each other online. To participate in the game, gamers need to purchase virtual FIFA money, known as “coins”, and set up a squad by purchasing virtual soccer players.

To do so, gamers participate in a primary market at the beginning of the game. FIFA itself provides the initial supply by selling random sets of players with mixed abilities, known as “packs”, for a fixed fee. Afterwards, gamers can exchange players on a secondary market. The latter is a continuous market, with an open limit-order book, and therefore also constitutes the focus of our study. Depending on the performance against their opponents, gamers are given a ranking in a leaderboard. If the ranking is high enough, they can sell their team to other gamers for real money. Also, gamers earn coins for each match they win. These monetary and reputational incentives are key features of the game that make it comparable to actual financial markets.

We also make this point more formally by developing a simple theoretical model. For simplicity and without loss of generality, we consider a transfer market with two types of soccer players, with high-skill or low-skill, respectively. As in the game, high-skill players are not only more talented than low-skill players, but also present in lower supply. As a result, they sell at a higher equilibrium price. Since ratings are fixed and predetermined, the two player types are uncorrelated assets.

Gamers are risk-averse, fully rational, and exhibit mean-variance utility over final wealth. The optimal portfolio of soccer players solves the following trade-off. On the one hand, high-skill players increase the quality of the team. On the other hand, their expensive nature reduces the size of the squad gamers are able to afford. In turn, a smaller squad provides less insurance against player injuries and suspensions during the game. Gamers then make two choices. First, they determine the optimal portfolio composition of high- and low-skill players. Second, they decide on the optimal amount of coin reserves to hold as a liquidity buffer, in case new players are needed.

In equilibrium, we show that all assets in this economy are priced by the security market line. Since there is no covariance risk across assets, however, the beta of any player simply reflects the ratio between the player’s volatility and total market volatility. This is an important result because it makes portfolio analysis meaningful in this market. Note also that none of the factor-model extensions to the security market line applies to this special case. Since fundamentals are predetermined and fixed, factors such as size and

\[3\text{See, e.g., http://www.gamstat.com.}\]
book-to-market, which some argue are correlated with latent state variables (Fama and French, 1995, 2004), should have no impact on returns in this market.

In the empirical analysis, we analyze daily and weekly prices for the entire year of trading of FIFA 19, which spans the period from September 2018 to August 2019. We perform two main types of asset pricing tests. First, we are able to construct a number of factor-mimicking portfolios that represent the cornerstone of modern asset pricing, such as those based on size and book-to-market (Fama and French, 1992), market beta (Frazzini and Pedersen, 2014), short-term mean reversion (Lo and MacKinlay, 1990), and volatility (Blitz and van Vliet, 2007). Interestingly, we find evidence in our sample for each of these asset pricing anomalies, even though there is by construction no change in the soccer players’ fundamentals during the one-year trading period we analyze.

To get a sense of the magnitude, consider the book-to-market anomaly. The Sharpe ratio of the long-short portfolio on value and growth stocks is 0.2 with daily data (see Kenneth French’s website). In our sample of daily observations, we obtain an estimate of 0.7. The larger number reflects the absence of fundamental news, which reduces trading and thus the standard deviation of returns, and also a zero in-game risk-free rate. To make a more instructive comparison, we transform these estimates into coefficients of variation, and obtain estimates of 5 and 1.43, respectively. Their ratio suggests that mispricing constitutes around one-third of the total volatility of real-life book-to-market portfolios.

Second, we are able to introduce a measure of investor sentiment that is orthogonal to the fundamental value of the assets. We consider the daily news sentiment index from Buckman et al. (2020), and study its relation with asset prices. Consistent with previous studies, we find that investor sentiment is associated with a contemporaneous increase in asset returns, and followed by mispricing correction (Baker and Wurgler, 2006, 2007; Baker, Wurgler, and Yuan, 2012). The novelty of our findings lies in the fact that they stem from a measure of sentiment that is genuinely uncorrelated with asset fundamentals. As a result, we lend strong support to the credibility of the results from the existing investor sentiment literature.

2. Model

We consider a two-period model. At time 0, agents need to build a squad to compete in the game, and start with a zero endowment of players. To participate in the transfer market, they need to purchase game-specific coins through cash. The thus attained amount of coins constitutes agent $j$’s initial wealth, denoted by $w_0$. The transfer market is characterized by perfect information, so there is nothing to learn from market prices.

For simplicity and without loss of generality, players can be of two types: high-skill or low-skill. High-skill players have a higher overall rating, defined as a numerical evaluation of their abilities, than low-skill players. Since ratings are fixed and predetermined, these player types are uncorrelated assets. The supply of high-skill players in the game is only a fraction of the supply of low-skill players. Due to the lower supply and higher ratings, high-skill players sell at a higher price.
At time 1, agents compete with each other in a series of games. At the end of the season, all teams are ranked in a leaderboard according to their overall performance. The final value of agent \( j \)'s team, denoted by \( \tilde{w}_{1j} \), is determined by the position of the team in the leaderboard, plus the amount of coin reserves (if any). This value can be exchanged for real cash.

Agents are risk-averse, and exhibit mean-variance utility over \( \tilde{w}_{1j} \). The optimal portfolio of players solves the following trade-off. On the one hand, high-skill players increase the quality of the team. On the other hand, their high price reduces the size of the squad agent \( j \) is able to afford. In turn, a smaller squad provides less insurance against player injuries and suspensions during the game.

Agents then make two choices. First, they determine the optimal portfolio composition of high- and low-skill players. Second, they decide on the optimal amount of coin reserves to hold as a liquidity buffer, in case new players are needed. Holding coins earns no returns, i.e., the risk-free rate is zero.

Investor \( j \) solves:

\[
\max_{\{\alpha_{Hj}, \alpha_{Lj}\}} E[u_j(\tilde{w}_{1j})] = E(\tilde{w}_{1j}) - \frac{\gamma_j}{2} \text{var}(\tilde{w}_{1j}),
\]

subject to:

\[
\tilde{w}_{1j} = w_{0j} \left( 1 + \sum_{i=L,H} \tilde{r}_i \alpha_{ij} \right),
\]

where \( \gamma_j \) is the coefficient of absolute risk-aversion, and \( \alpha_{ij} \) is the fraction of wealth invested in asset \( i \). Note that high-skill players exhibit a higher first and second moment of returns (i.e., \( \bar{r}_H > \bar{r}_L \) and \( \sigma^2_H > \sigma^2_L \)).

In Appendix A, we show that all assets in this economy are priced by the security market line. The betas, however, have a different interpretation than usual. Since there is no covariance risk across assets, the beta of asset \( i \) simply reflect the ratio between the asset \( i \)'s volatility and total market volatility.

**Appendix A**

The first two moments of the distribution of final wealth are:

\[
E(\tilde{w}_{1j}) = (1 + \bar{r}_H \alpha_{Hj} + \bar{r}_L \alpha_{Lj}) w_{0j},
\]

\[
\text{var}(\tilde{w}_{1j}) = \left( \sigma^2_H \alpha^2_{Hj} + \sigma^2_L \alpha^2_{Lj} \right) w_{0j}^2,
\]

where \( \alpha_{ij} \) is the ratio between demand for asset \( i \), \( a_{ij} \), and current wealth \( w_{0j} \). Note that the covariance between the two assets is zero (i.e., \( \sigma_{HL} = 0 \)). The two first-order conditions yield:

\[
\bar{r}_H = \gamma_j \sigma^2_H \alpha_{Hj} w_{0j},
\]

\[
\bar{r}_L = \gamma_j \sigma^2_L \alpha_{Lj} w_{0j}.
\]

Solving out, the optimal investments are:

\[
\alpha_{Hj} w_{0j} = \frac{\bar{r}_H}{\gamma_j \sigma^2_H} \equiv a^*_H j,
\]

\[
\alpha_{Lj} w_{0j} = \frac{\bar{r}_L}{\gamma_j \sigma^2_L} \equiv a^*_L j.
\]
which implies the same portfolio formation \( \left( \frac{\alpha_j^*}{\alpha_{L,j}} \right) \) for all investors.

To derive equilibrium returns, take the first-order condition and sum up across all investors:

\[
\sum_{j=1}^{M} \tau_j \bar{r}_H = \sigma_H^2 \sum_{j=1}^{M} \bar{a}_{H,j}, \tag{A.7}
\]

\[
\sum_{j=1}^{M} \tau_j \bar{r}_L = \sigma_L^2 \sum_{j=1}^{M} \bar{a}_{L,j}, \tag{A.8}
\]

where \( \tau_j \equiv \frac{1}{\gamma_j} \) represents investor \( j \)'s risk tolerance.

We can divide by all investors \( (M) \), and apply the equilibrium conditions \( \bar{a}_{H,j}^* \equiv \bar{a}_H, \bar{a}_{L,j}^* \equiv \bar{a}_L \):

\[
\tau_M \bar{r}_H = \sigma_H^2 \bar{a}_H, \tag{A.9}
\]

\[
\tau_M \bar{r}_L = \sigma_L^2 \bar{a}_L, \tag{A.10}
\]

where \( \tau_M \) is the average level of risk tolerance. Rearranging, we obtain:

\[
\bar{r}_H^* = \frac{\bar{a}_H}{\tau_M} \sigma_H^2, \tag{A.11}
\]

\[
\bar{r}_L^* = \frac{\bar{a}_L}{\tau_M} \sigma_L^2. \tag{A.12}
\]

Now, define market returns as:

\[
\bar{r}_M = \frac{\bar{a}_H}{\bar{a}_M} \bar{r}_H + \frac{\bar{a}_L}{\bar{a}_M} \bar{r}_L, \tag{A.13}
\]

where \( \bar{a}_M \equiv \bar{a}_H + \bar{a}_L \). Note that the covariance between the returns on asset \( i \) and market returns is:

\[
cov(\bar{r}_H, \bar{r}_M) \equiv \sigma_{HM} = \frac{\bar{a}_H}{\bar{a}_M} \sigma_H^2, \tag{A.14}
\]

\[
cov(\bar{r}_L, \bar{r}_M) \equiv \sigma_{LM} = \frac{\bar{a}_L}{\bar{a}_M} \sigma_L^2. \tag{A.15}
\]

Then we can rewrite returns as:

\[
\bar{r}_H^* = \frac{\bar{a}_M}{\tau_M} \sigma_{HM}, \tag{A.16}
\]

\[
\bar{r}_L^* = \frac{\bar{a}_M}{\tau_M} \sigma_{LM}. \tag{A.17}
\]

But then the relation must hold also for the market portfolio:

\[
\bar{r}_M^* = \frac{\bar{a}_M}{\tau_M} \sigma_M^2, \tag{A.18}
\]

which implies:

\[
\frac{\bar{a}_M}{\tau_M} = \frac{\bar{r}_M^*}{\sigma_M^2}. \tag{A.19}
\]

Using this result, we can finally rewrite returns as:

\[
\bar{r}_H^* = \sigma_{HM} \frac{\bar{r}_M^*}{\sigma_M^2} \equiv \beta_H \bar{r}_M^*, \tag{A.20}
\]

\[
\bar{r}_L^* = \sigma_{LM} \frac{\bar{r}_M^*}{\sigma_M^2} \equiv \beta_L \bar{r}_M^*. \tag{A.21}
\]
which represents the security market line. Note that betas are just a function of volatility:

$$\beta_H = \frac{\bar{a}_H \sigma_H^2}{\left(\bar{a}_M \sigma_M^2\right)^2 + \left(\bar{a}_H / \bar{a}_M \right)^2 \sigma_L^2}$$  \hspace{1cm} (A.22)

$$\beta_L = \frac{\bar{a}_L \sigma_L^2}{\left(\bar{a}_M \sigma_M^2\right)^2 + \left(\bar{a}_L / \bar{a}_M \right)^2 \sigma_H^2}.$$  \hspace{1cm} (A.23)

References


