Risk, return, and sentiment in a virtual asset market

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Joint-hypothesis problem

The **joint-hypothesis problem** casts doubt on the results of market efficiency research (Fama, 1970, 1991).
$\longrightarrow$ is the market wrong or the model

Specifically, it is hard to assess to what extent stock prices reflect:

- economic fundamentals;
- mispricing.

Economic fundamentals

One approach is to identify fundamentals through **factor** models.
$\longrightarrow$ long-short portfolios

Intuition: capture sources of **common variation** of returns that are otherwise latent, such as a distress factor (Fama and French, 2004).

It is not entirely clear, however, whether such factors also represent **mispricing** to some extent (see, e.g., Daniel and Titman, 1997; Stambaugh et al., 2012; McLean and Pontiff, 2016).

Sentiment

A different approach is to try and identify mispricing directly.
$\longrightarrow$ Proxy: **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).

Sentiment (cont'd)

This process typically involves the creation of an **index** (Carroll et al., 1994; Baker and Wurgler, 2006, 2007; Baker et al., 2012).

The issue with these measures, however, is that they may partly reflect economic **fundamentals** (see, e.g., DeVault et al., 2019).
$\longrightarrow$ back to square one!

What we do

In this paper, we propose a **novel solution** to the joint-hypothesis problem.

We identify:

- a credible and ex-ante distinction between
  (A) fundamentals
  (B) investor behavior
- the relative impact of the two on asset returns (B/A).

Intuition: how much are returns driven by (B) rather than (A)?

What we do (cont'd)

Specifically, we consider a large virtual asset market from the **FIFA 19** video game, in which fundamentals are:

- Predetermined.
  – before trading starts
- Publicly known.
  – everyone observes them

This allows us to directly assess the impact of investor behavior on price formation independently of economic fundamentals.

$\longrightarrow$ unique setting to carry out asset pricing tests!

What we find

We find three main empirical results:

- **Factors** such as size and book-to-market price returns in this market, despite the absence of systematic risk.
- **Sentiment** has a substantial impact on asset prices that is orthogonal to fundamentals.
- **Attention** also plays an important role in the price formation process.

The results are robust to a large number of specifications.

What we find (cont'd)

The estimates suggest that prices in **real-life** financial markets include a substantial behavioral component.
$\longrightarrow$ about $1/3$ 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).

FIFA 19

The FIFA game

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;
- played by 36 million gamers.

The FIFA game (cont'd)

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, users can:

- purchase virtual FIFA money, known as **coins**;
- set up a **squad** by signing virtual soccer players.

Player market

At the beginning of the season, gamers participate in a **primary** market for players.

FIFA itself provides the initial supply by selling random sets of players with mixed abilities (known as **packs**).
– available for a fixed fee

Afterwards, gamers can exchange players on a **secondary** market similar to a stock exchange:
– continuous
– open limit-order book
– fixed short-term supply.

Financial incentives

In addition to the utility of playing the game itself, gamers have two important **financial incentives**:

- First, they **earn coins** for each match they win.
- Second, they can **sell their team** to other users through an active market for FIFA accounts (see, e.g., Playerauctions.com).

Position in the leaderboard $\longrightarrow$ monetary value of the team.

Financial incentives (cont'd)

These monetary and reputational incentives make the game comparable to actual financial markets.

Attesting to the relevance of the financial component of the game:

- there is an **active online community** on investing including several prolific influencers;
- gamers **exchange tips** on how to maximize returns from trading players (see, e.g., Futchief.com).

Demographics

Finally, it is also important to note that the gamers' **demographics** are similar to those of real investors.

The Entertainment Software Association (ESA) states that the average gamer is:
– 34 years old;
– male;
– college educated.

Finance research finds similar characteristics (see, e.g., Barber and Odean, 2001; Bauer et al., 2009; Grinblatt et al., 2011).

Theory

Players are dividend-paying assets with finite maturity:

- $Prob(win = 1) = f(\overline{Rating})$
- $\overline{Rating} = \frac{1}{n}\sum_{i=1}^{n} Rating_i$

Mean-variance optimizing gamers face the following **trade-off**:

- Small number of players with high quality;
- Large number of players with low quality.

In this economy:

- Assets are priced by the security market line;
- Beta = ratio between player and market volatility (cov. risk = 0).

Data

Sample

We retrieve price data for all players traded in the FIFA 19 FUT market.

- **Period**: September 22, 2018, to September 19, 2019.
- **Source**: "Futbin", a third party that aggregates FUT statistics.
- **Platform**: PlayStation market (for liquidity reasons).

In total, we obtain 361 daily observations for 20,941 players.
– 156 countries
– 632 clubs
– 43 national leagues.

Restricted sample

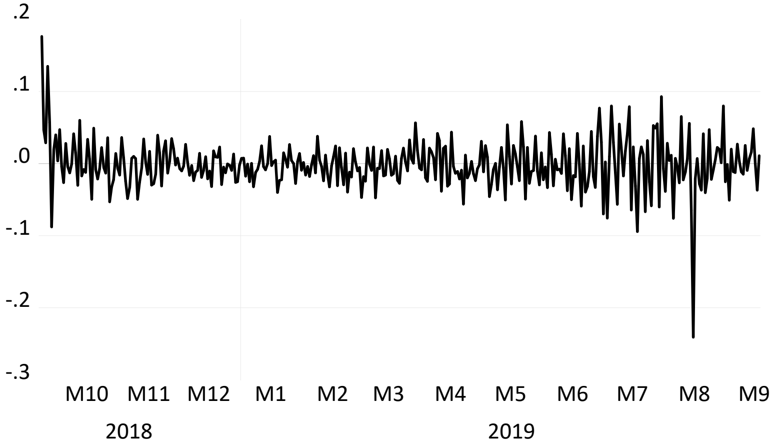
We limit the analysis to currently active players with the highest ratings, labeled as the **gold** category.

Then we exclude:

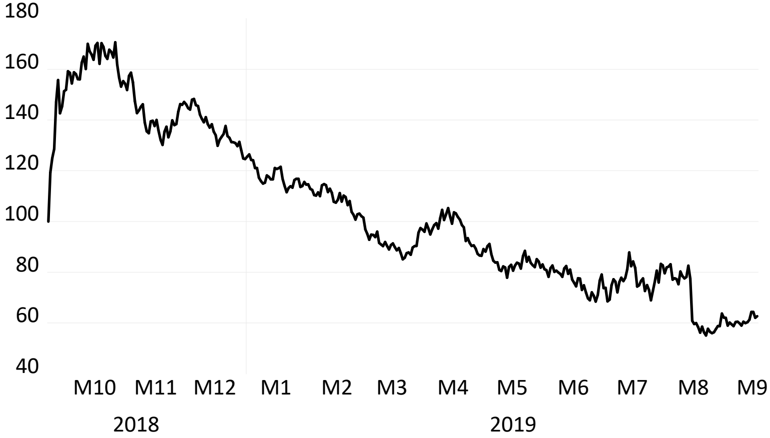
- famous players from the past that are no longer active in real life, known as **icons**.
- players with **stale prices** (i.e., zero daily returns).

In so doing, we obtain a final sample of 1,994 unique players.

Player returns over time



Player prices over time



Prices

Prices and ratings

Preliminary analysis: relation between **player prices** and **ratings**.

- see if gamers know what they're doing

To this end, we acknowledge the fact that the supply of players is inversely related to their ratings.

- primary market creates convex relation

Hence, our **test equation** is as follows:

$$log(P_{i,t}) = \alpha + \beta_1 Rating_i + \underbrace{\beta_2}_{>0} Rating_i^2 + \eta_t + \varepsilon_{i,t}, \quad (1)$$

Main results

	Panel A: Full sample				Panel B: November-July			
	Linear	Convex	Time FE	FMB	Linear	Convex	Time FE	FMB
Rating	0.253***	-3.954***	-3.954***	-3.954***	0.253***	-4.096***	-4.096***	-4.096***
	(35.200)	(-19.009)	(-19.005)	(-85.475)	(34.706)	(-19.183)	(-19.180)	(-90.061)
$Rating^2$		0.026***	0.026***	0.026***		0.027***	0.027***	0.027***
		(19.973)	(19.970)	(90.195)		(20.112)	(20.108)	(95.313)
$Adj.R^2$	0.566	0.695	0.717	0.723	0.589	0.732	0.752	0.755
Obs	719,834	719,834	719,834	719,834	544,362	544,362	544,362	544,362

Main results (cont'd)

	Panel C: Rating <90				Panel D: Weekly data			
	Linear	Convex	Time FE	FMB	Linear	Convex	Time FE	FMB
Rating	0.238***	-4.989***	-4.989***	-4.989***	0.247***	-4.022***	-4.022***	-4.022***
	(33.082)	(-29.309)	(-29.304)	(-90.354)	(30.774)	(-17.108)	(-17.110)	(-32.100)
$Rating^2$		0.033***	0.033***	0.033***		0.027***	0.027***	0.027***
		(30.438)	(30.433)	(94.077)		(17.963)	(17.965)	(33.860)
$Adj.R^2$	0.517	0.664	0.690	0.699	0.550	0.685	0.704	0.712
Obs	714,780	714,780	714,780	714,780	103,688	103,688	103,688	103,688

Factors

Market beta

We start the analysis of returns by estimating a fifty-day rolling **market-beta** for each player:

$$r_{i,t} = \alpha + \beta r_{m,t} + \varepsilon_{i,t}, \tag{2}$$

where:

- $r_{i,t}$ is the log-return of player i on day t;
- $r_{m,t}$ is the log-return on the market index.
  – equal-weighted index of all players in the sample
  – normalized to 100 on the first day of the sample period

Subsequently, we rank players on their market beta and form **decile portfolios** (daily/weekly rebalancing).

Market beta (cont'd)

	Market beta portfolios										
	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D10-D1
Daily	0.001	0.002	0.002	0.003	0.002	0.001	0.001	-0.001	-0.002	-0.005	-0.006
	(0.188)	(0.658)	(0.474)	(0.808)	(0.354)	(0.152)	(0.131)	(-0.099)	(-0.236)	(-0.560)	(-0.697)
Weekly	0.001	0.001	0.002	0.002	0.001	0.001	0.001	0.001	0.000	-0.001	-0.002
	(0.093)	(0.157)	(0.156)	(0.203)	(0.041)	(0.052)	(0.045)	(0.030)	(-0.019)	(-0.057)	(-0.131)

- Market beta is not priced, or at least in unconditional tests.

Size

Although we do not have data on the supply of players, we can measure **size** using the price level $P_{i,t}$ itself.

The reason is as follows:

- The supply of high-skill players is a fraction of the supply of low-skill players (they are scarce) $\longrightarrow n_H < n_L$.
- However, the convex relation between prices and ratings more than compensates the supply effect $\longrightarrow P_H > P_L$

The net effect makes high-skill players "large caps".
$\longrightarrow n_H P_H > n_L P_L$.

Size (cont'd)

	Size portfolios											
	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D10-D1	T50-B50
Daily	0.033	0.038	0.036	0.028	0.011	-0.010	-0.022	-0.029	-0.052	-0.022	-0.055***	-0.057***
	(6.649)	(6.019)	(4.853)	(3.833)	(1.585)	(-1.471)	(-3.069)	(-3.923)	(-8.271)	(-6.995)	(-9.434)	(13.681)
Weekly	0.016	0.016	0.014	0.011	0.007	0.001	-0.006	-0.013	-0.026	-0.011	-0.026	-0.024***
	(1.140)	(0.900)	(0.723)	(0.596)	(0.396)	(0.050)	(-0.326)	(-0.707)	(-1.584)	(-1.308)	(-1.656)	(6.634)

- Strong size effect in player returns!
- Note: this has nothing to do with systematic risk.

Book-to-market

Next, we look into the book-to-market ratio.

Although players in FUT do not formally have a "book" value, we calculate it as follows:

$$BM_{i,t} = \underbrace{(\alpha + \beta_1 Rating_i + \beta_2 Rating_i^2)}_{\text{FMB fitted values}} - ln(P_{i,t}), \tag{3}$$

using the estimated coefficients α, β_1, and β_2 from the Fama-MacBeth regressions to avoid a look-ahead bias.

Book-to-market (cont'd)

	Book-to-market portfolios											
	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D10-D1	T30-B30
Daily	-0.070	-0.039	-0.026	-0.009	0.007	0.018	0.026	0.031	0.033	0.034	0.104***	0.078***
	(-12.046)	(-5.911)	(-4.130)	(-1.411)	(1.009)	(2.757)	(4.153)	(5.595)	(6.830)	(8.623)	(19.437)	(18.355)
Weekly	-0.031	-0.017	-0.008	-0.002	0.004	0.008	0.011	0.015	0.015	0.015	0.046***	0.034***
	(-2.115)	(-1.086)	(-0.501)	(-0.099)	(0.222)	(0.450)	(0.651)	(0.933)	(1.074)	(1.302)	(3.335)	(9.207)

- Strong book-to-market effect in player returns!
- Again, this has nothing to do with systematic risk.

In the paper we also show the presence of the short-term mean reversion and low volatility factors.

Real-world comparison

It is instructive to compare the magnitude of these premia with those from the real world.

For **book-to-market** returns, the annualized **Sharpe ratios** are:

- SR = 0.16 in the real world (07/1926–12/2019, EW, 30%);
- SR = 0.49 in the FUT market ($\sigma \downarrow$ due to no fundamental news).

To make the comparison more instructive, consider the **coefficients of variation** (CV = 1 / SR):

- CV = 2.05 in the FUT market;
- CV = 5.81 in the real world.

The ratio is 2.05/5.81 = 35% $\longrightarrow$ mispricing explains **one-third** of total volatility of the real-life value premium.

Characteristics

Next, we study the direct effect of the **characteristics** rather than portfolios.

Then we estimate Fama-MacBeth regressions including:

- first one characteristic at a time;
- then all characteristics together.

(The results are similar using fixed-effects regressions)

Characteristics (cont'd)

Dependent: Ret	1	2	3	4	5	6	7 (M11-M07)	8 (<90)	9 (weekly)
Beta(-1)	-0.001					0.000	0.001	0.000	-0.001
	(-0.726)					(0.022)	(0.726)	(0.037)	(-0.239)
Log(BM(-1))		0.460***				0.340***	0.351***	0.376***	0.538***
		(19.056)				(15.874)	(14.642)	(14.730)	(5.495)
Log(P(-1))			-0.017***			-0.008***	-0.008***	-0.005***	-0.029***
			(-8.251)			(-5.005)	(-4.407)	(-2.460)	(-4.502)
Ret(-1)				-0.120***		-0.092***	-0.074***	-0.093***	-0.372***
				(-8.834)		(-7.540)	(-5.373)	(-7.668)	(-19.277)
Log(Vol(-1))					-0.016***	-0.009***	-0.011***	-0.009***	-0.019***
					(-4.502)	(-3.984)	(-4.223)	(-3.910)	(-4.018)
$Adj.R^2$	0.048	0.046	0.041	0.060	0.053	0.172	0.181	0.176	0.285
Obs	618,140	618,140	618,140	618,140	618,140	618,140	522,428	604,810	87,736

Sentiment

Sentiment

Previous studies on **sentiment** consider:

- Direct effect on stock returns (Baker and Wurgler, 2006, 2007).
- Interaction with characteristics (Stambaugh et al., 2012).

In this paper, we consider a measure of sentiment that is **perfectly orthogonal** to the asset market under consideration.

We take the **news sentiment** measure from Buckman et al. (2020), which grants two advantages:

- Captures the general level of sentiment in the media at large.
- Available at the daily frequency for our entire sample period.

Sentiment (cont'd)

Dependent: Ret	1	2	3	4	5	6	7
dSENT	0.070***						
	(3.705)						
dSENT(-1)		-0.303***					
		(-16.503)					
dSENT(-1) × Beta(-1)			-0.074***				
			(-6.250)				
dSENT(-1) × log(BM(-1))				-1.172***			
				(-4.139)			
dSENT(-1) × log(P(-1))					0.170***		
					(13.297)		
dSENT(-1) × Ret(-1)						-1.453***	
						(-9.941)	
dSENT(-1) × log(Vol(-1))							-0.035***
							(-3.160)
$Adj.R^2$	0.066	0.066	0.258	0.258	0.258	0.258	0.258
Obs	591,607	591,607	591,607	591,607	591,607	591,607	591,607
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	No	Yes	Yes	Yes	Yes	Yes
Player FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Attention

Attention

Apart from sentiment, **attention** is another important phenomenon in the behavioral asset pricing literature. Da et al. (2011) show that **Google search intensity** is associated with higher prices.

In this paper, we replicate this study using Google Trends along with some "attention-grabbing attributes":

- the (cumulative) **number of goals** a player scores in real life in the national league;
- an indicator of whether the player is performing exceptionally well in real life as assessed through the **TOTW selection**.

Attention and returns

Dependent: Ret	1	2	3	4	5 (M11-M07)	6 (<90)
dGT	0.014***			0.010**	0.015***	0.011**
	(3.099)			(2.282)	(3.254)	(2.302)
TOTW		0.415***		0.416***	0.414***	0.424***
		(24.649)		(24.550)	(24.138)	(24.631)
Goals			0.005***	0.006***	0.006***	0.006***
			(5.234)	(5.413)	(5.904)	(5.390)
Beta(-1)	-0.009***	-0.009***	-0.009***	-0.010***	-0.012***	-0.010***
	(-8.221)	(-8.355)	(-8.069)	(-8.660)	(-10.473)	(-8.777)
log(BM(-1))	1.963***	2.027***	2.040***	1.925***	1.788***	2.005***
	(28.480)	(30.702)	(30.886)	(27.913)	(22.475)	(25.457)
log(P(-1))	-0.061***	-0.040***	-0.040***	-0.065***	-0.095***	-0.056***
	(-6.896)	(-4.754)	(-4.733)	(-7.425)	(-9.241)	(-5.523)
Ret(-1)	-0.264***	-0.271***	-0.270***	-0.264***	-0.278***	-0.264***
	(-53.226)	(-54.990)	(-54.657)	(-53.470)	(-54.290)	(-53.203)
log(Vol(-1))	-0.021***	-0.019***	-0.019***	-0.021***	-0.028***	-0.021***
	(-19.881)	(-17.838)	(-17.901)	(-20.028)	(-26.279)	(-19.780)
$Adj.R^2$	0.342	0.344	0.337	0.350	0.351	0.351
Obs	82,425	84,074	84,074	82,425	71,259	81,823
Player FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Concluding remarks

Concluding remarks

In this paper, we propose a novel approach to the joint-hypothesis problem.

We analyze the price formation process from a large virtual market for soccer players in the online video game FIFA 19.

The video game has two important features for asset pricing research:

- structure and demographics are similar to real-life financial markets;
- fundamentals are predetermined and publicly known.

Concluding remarks (cont'd)

We find three main empirical results:

- First, a number of factors such as size and book-to-market price returns in this market, despite the absence of systematic risk.
- Second, sentiment has an independent and substantial impact on asset prices.
- Third, attention plays an important role in the price formation process.

The results suggest that prices in real-life financial markets include a substantial behavioral component (= one-fifth to one-half).

Thanks for your attention!