Pontifícia Universidade Católica
do Rio de Janeiro

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Essays on Herding

Tese de Doutorado

Thesis presented to the Programa de Pós-Graduação em Administração de Empresas of the Departamento de Administração, PUC-Rio as partial fullfilment of the requirements for the degree of Doutor em Administração de Empresas

Advisor: Prof. Marcelo Cabús Klötzle

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Abstract

Raimundo Júnior, Gerson de Souza; Klötzle, Marcelo Cabús (Advisor).**Essays on Herding**. Rio de Janeiro, 2022. 73p. Ph.D. Dissertation – Departamento de Administração – Pontifícia Universidade Católica do Rio de Janeiro.

Herding is a feature of investor behavior in financial markets, particularly in market stress. In the thesis we will apply an approach based on the transversal dispersion of individual stock betas, which allows us to extract herd patterns, using two dynamic methodologies to measure the herd phenomenon over time with a state-space model in three different markets.

The first study analyzes beta herding in the Brazilian stock market using a state-space model, controlled by two groupings of companies: those stocks listed on the market index (Ibovespa) and those listed on the stock exchange as a whole. The findings revealed a high herd on the Brazilian stock exchange, with only small differences between the clusters. Regarding the control variables, we found that the dividend yield, market volatility, SMB, and WML factors were significant for both groups, indicating that the herd is significant regardless of the behavior of these variables.

The second study examines beta herding in the commodity market, using the methodology developed by Hwang and Salmon (2004) and a beta adaptation standardized by Hwang, Rubesam, and Salmon (2018). We analyzed the behavior of fifteen commodities between 2000 and 2018 and then extracted the food commodities to test their effect separately. The results suggest that betas can deviate from fundamentals in both samples. However, food commodity betas tend to revert more quickly to stability between demand and supply, which results in a long-term risk-return balance.

The third study applies the methodology of Hwang and Salmon (2004) and a beta adaptation standardized by Hwang, Rubesam, and Salmon (2018) for the Cryptocurrency market. The results reveal that the herd towards the market presents significant movement and persistence regardless of the market condition, expressed through the market index, market volatility, and volatility index. When analyzing trail herding, it is possible to observe that herding was intense during the investigated period. We also identified a positive relationship between herding and market stress.

Keywords

State-space; Herding; Commodities; Cryptocurrencies; Fear

Resumo

Raimundo Júnior, Gerson de Souza; Klötzle, Marcelo Cabús (Advisor). **Ensaios sobre Efeito-Manada**. Rio de Janeiro, 2022. 73p. Ph.D. Dissertation – Departamento de Administração – Pontifícia Universidade Católica do Rio de Janeiro.

O efeito-manada é uma característica do comportamento do investidor nos mercados financeiros, particularmente no estresse do mercado. Na tese aplicaremos uma abordagem baseada na dispersão transversal de ações betas individuais, que nos permite extrair padrões de efeito-manada, usando duas metodologias dinâmicas para medir o fenômeno manada ao longo do tempo com um modelo de espaço de estados em três mercados diferentes.

O primeiro estudo analisa o beta herding no mercado de ações brasileiro usando um modelo de estado-espaço, controlado por dois agrupamentos de empresas: as empresas listadas no índice de mercado e as listadas na bolsa como um todo. Os achados revelaram um efeito-manada elevado na bolsa brasileira, com apenas pequenas diferenças entre os clusters. Em relação às variáveis de controle, verificamos que os fatores dividend yield, volatilidade do mercado, SMB e WML foram significativos para ambos os grupos, indicando que o herding é significativo independente do comportamento dessas variáveis.

O segundo estudo examina o beta herding no mercado de commodities, utilizando a metodologia desenvolvida por Hwang e Salmon (2004) e uma adaptação do beta padronizado por Hwang, Rubesam e Salmon (2018). Analisamos o comportamento de quinze commodities entre 2000 e 2018 e, em seguida, extraímos as commodities alimentares para testar seu efeito separadamente. Os resultados sugerem que os betas podem se desviar dos fundamentos em ambas as amostras. No entanto, os betas de commodities alimentares tendem a reverter mais rapidamente para a estabilidade entre demanda e oferta, o que resulta em um equilíbrio risco-retorno de longo prazo.

O terceiro estudo aplica a metodologia de Hwang e Salmon (2004) e uma adaptação beta padronizada por Hwang, Rubesam e Salmon (2018) para o mercado de Criptomoedas. Os resultados revelam que o efeito-manada em direção ao mercado apresenta significativa movimentação e persistência independentemente da condição de mercado, expressa através do índice de mercado, volatilidade de mercado e índice de volatilidade. Ao analisar o efeito-manada, é possível observar que o efeito-manada foi intenso durante o período investigado. Também identificamos uma relação positiva entre o estresse de mercado e efeito-manada.

Palavras-chave

Estado-Espaço; Efeito-Manada; Commodities; Criptomoedas; Medo

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1
Introduction

Understanding the decision-making process of the various market participants is a great challenge for both academic researchers and market professionals. One of the areas that fall within this problem involves the herd behavior of investors. In the behavioral finance literature, investors tend to exhibit the herd effect when they decide to follow the observed decisions of other investors or market movements without regard to their own beliefs, judgments, or information.

As a consequence, groups of investors tend to move in the same direction and generate price deviations away from their fundamentals, causing short-term trends in prices and excess volatility in the market Bikhchandani, Hirshleifer et al. (1992), Nofsinger and Sias (1999).

The herding effect can result from a rational act of investors maximizing their expected utility or an irrational act derived from interactions between investors. Bikhchandani and Sharma (2000) make a distinction between investors who are confronted with the same range of information originating from economic fundamentals ('spurious' herd effect) and investors who intentionally copy the behavior of others ('intentional' herd effect).

Herding generates price deviations and creates implications for trading strategies and asset pricing models. Furthermore, such deviations can generate speculative bubbles, accelerate crises and distort the perception of investors (institutional and individual) in the acceptance of government regulatory policies and transparency of company information.

2
Political risk, fear, and herding on the Brazilian stock exchange

2.1
Introduction

Herding is defined as a situation in which investors abandon their own beliefs and information and decide to imitate the observed decisions of their peers or movements in the market (Hwang and Salmon 2004). Bikhchandani and Sharma (2000) make a distinction between spurious and intentional herding. Whereas in intentional herding, investors have a strong willingness to copy the behaviors of others in the market, in spurious herding, investors take similar actions when exposed to the same information set driven by fundamentals.

Empirical evidence on herding depends on the group of countries or the type of investor included in the analysis. Humayun Kabir and Shakur (2018) found that investors in most Asian and Latin American stock markets herd when volatility is high, except Argentina and Brazil. Solakoglu and Demir (2014) found evidence of herding in Borsa Istanbul only for the group of small- to medium-sized companies. Hwang and Salmon (2004) studied beta herding in the US and the Korean stock markets. For both markets, they concluded that herding showed significant movements and persistence, with no relation to given markets conditions and macro factors. It was also present under bear and bull conditions. Chen (2013) studied herding behavior in 63 developed, developing and frontier markets, and despite finding beta herding in all markets, no significant differences were found between these groups on average. Choi and Skiba (2015) analysed herding behavior of institutional investors in 41 countries and found evidence that institutional herding is greater in markets characterized by a higher level of information transparency, suggesting that spurious herding is more prevalent among this class of investors.

Due to the controversial results in the literature, it is essential to include a more in-depth analysis of specific markets. In this sense, Brazil has a strong developed stock market among the emerging ones, ranking in the first position among Latin American markets, including Mexico, in regard to market capitalization (World Federation of Exchanges, 2019)

The question then arises whether there is a herd effect in the Brazilian stock market, controlled by different groupings of companies. This study employs the beta-herding approach, using the methodology developed by Hwang, Rubesam, and Salmon (2018), in a state–space model. The study is unique in that it adds other control variables when estimating the herding effect, such as political risk and the volatility index, and uses a novel method for herding measurement.

2.2
Methodology

This study investigates the occurrence of herding in the Brazilian stock market between January 2004 and December 2017, considering two company groupings: those listed on the market index (IBOVESPA), and those listed on the stock market as a whole, excluding companies listed on the Ibovespa (BOLSA). We decided to discriminate between IBOVESPA and nonIBOVESPA constituents, as the IBOVESPA covers the most liquid (around 50) stocks traded on the Brazilian stock market, which turns out to be also those with a higher market capitalization. We extracted stock price data from the Economatica database; from the Brazilian Center for Research in Financial Economics of the University of São Paulo (Nefin) we obtained data for Rm (market return), SMB (Small minus Big), WML (Winners minus Losers), Dividend Yield (DY), and Volatility Index (IVOL)[1] ; Bloomberg supplied the term structure of interest rates (TSIR)[2] , and the PRS Group provided the Political Risk Index (ICRG)[3] .

We apply the state–space methodology proposed by Hwang and Salmon (2004), and the standardised beta measurement based on Hwang, Rubesam, and Salmon (2018).

According to Hwang and Salmon (2004), when herding occurs, the β coefficient must be corrected in accordance with equation (1), which empirically extracts the sentimental herding (h_{mt}):

$$\frac{E_t^b(r_{it})}{E_t^b(r_{mt})} = \beta_{imt}^b = \beta_{imt} - h_{mt}(\beta_{imt} - 1) \qquad (1)$$

[1] Similar to VIX. The detailed methodology is in http://www.nefin.com.br/volatility_index.html.

[2] Calculated as the difference between the annualized 10-year interest rate and the annualized monthly interest rate.

[3] For additional details, refer to Bekaert et al. (2014).

where $E_t^b\,(r_{it})$ and β_{imt}^b are the short-term conditional biased market expectation regarding excess returns from asset *i* and its beta at time *t*, respectively, and h_{mt} is the latent herd effect parameter that varies with time, with $h_{mt} \leq 1$ and conditional on market fundamentals. In general, when $0 < h_{mt} < 1$, there is some degree of herd effect, determined by the magnitude of h_{mt}. In the case of no *herding* in equation (1), $\beta_{imt}^b = \beta_{imt}$ (Hwang and Salmon 2004).

As a measure of beta-herding, we propose the standardised beta:

$$H_t^* = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{\widehat{\beta_{it}^b} - \overline{\widehat{\beta_{it}^b}}}{\hat{\sigma}_{\widehat{\beta_{it}^b}}}\right)^2 = V_{c-norm}(\,\beta_{imt}^b) \qquad (2)$$

where $\overline{\widehat{\beta_{it}^b}}$ is the average of the betas, N is the number of assets, $\hat{\sigma}_{\widehat{\beta_{it}^b}}$ is the standard error of $\widehat{\beta_{it}^b}$, and V_{c-norm} is the Normalised Variance.

Substituting 1 in 2, and given that the cross-sectional mean of β_{imt}^b is always 1, we have:

$$H_t^* = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{\beta_{imt} - \ h_{mt}(\beta_{imt} - 1) - 1}{\hat{\sigma}_{\widehat{\beta_{it}^b}}}\right)^2$$

$$H_t^* = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{\beta_{imt} - 1}{\hat{\sigma}_{\widehat{\beta_{it}^b}}}\right)^2 (1 - h_{mt})^2$$

$$\ln\,(H_t^*) = \ln\left[V_{c-norm}(\,\beta_{imt}^b)\right] + 2\ln\,(1 - h_{mt})$$

This implies:

$$h_{mt} = 1 - \sqrt{\exp\,(H_{mt})}$$

For the same Hwang and Salmon (2004) argument:

$$\ln\left[V_{c-norm}(\,\beta_{imt}^b)\right] = \ \mu_m + \upsilon_{mt}$$

Following Hwang and Salmon (2004), we rewrite equation (1) in the form of state–space by altering the beta herding measure proposed by equation (2). This leads to the following formulation:

$$\ln\,(H_t^*) = \ \mu_m + H_{mt} + \upsilon_{mt} \qquad (3)$$

where μ_m is a short-term constant and H_{mt} follows an AR (1) process. On this basis, five state–space models will be estimated in this study. Model (1) will be estimated as per equation (4).

(Model 1)

$$\ln(H_t^*) = \mu_m + H_{mt} + \upsilon_{mt}$$
$$H_{mt} = \phi H_{mt-1} + \eta_{mt} \tag{4}$$

Equation (4) represents the basic state–space model based on Kalman's filter method. A statistically significant H_{mt} value may be understood as representing the herd effect and a significant value of ϕ particularly supports an autoregressive model of herding.

Model (2) adds the market volatility ($ln\,\sigma_{mt}$) and the market return (r_{mt}) to equation (4), as independent variables.

(Model 2)

$$\ln(H_t^*) = \mu_m + H_{mt} + \theta_{c1}\ln(\sigma_{mt}) + \theta_{c2}\mathrm{r}_{mt} + \upsilon_{mt}$$
$$H_{mt} = \phi H_{mt-1} + \eta_{mt} \tag{5}$$

We estimate model (3) by adding the Small minus Big (SMB), High minus Low HML, and Winners minus Losers (WML) factors to model (2):

$$\ln(H_t^*) = \mu_m + H_{mt} + \theta_{c1}\ln(\sigma_{mt}) + \theta_{c2}\mathrm{r}_{mt} + \theta_{c3}SMB + \theta_{c4}\,HML + \theta_{c5}\,WML + \upsilon_{mt}$$
$$H_{mt} = \phi H_{mt-1} + \eta_{mt} \tag{6}$$

Model (4) is estimated with the market variable Dividend Yield (DY) and a variable of market sentiment, Political Risk (RISK):

(Model 4)

$$\ln(H_t^*) = \mu_m + H_{mt} + \theta_{c1}\ln(RISK) + \theta_{c2}DY + \upsilon_{mt}$$
$$H_{mt} = \phi H_{mt-1} + \eta_{mt} \tag{7}$$

Model (5) is estimated with the market variable term structure of interest rate (TSIR) and a variable of market sentiment, the volatility index (IVOL)[4] :

(Model 5)

$$\ln(H_t^*) = \mu_m + H_{mt} + \theta_{c1}\mathrm{IVOL} + \theta_{c2}\, ETJ + \upsilon_{mt}$$

$$H_{mt} = \phi H_{mt-1} + \eta_{mt} \tag{8}$$

2.3
Results

Table 1 presents the descriptive statistics of the standardized beta and the control variables.

We found a higher mean and standard deviation for the standardized beta – $LN(H_t^*)$– of IBOVESPA, which was expected, since IBOVESPA stocks are the largest of the market, hence commanding higher volume and, presumably a higher volatility.17

Given the structure of the Brazilian market, with high concentration, high informational asymmetry, low liquidity and a low volume, local investors take positions in the largest market shares, causing them to be driven by sentimental herding. However, the Ibovespa companies have a greater volume of trading than the Bolsa companies; most Brazilian institutions invest in these assets; and derivative instruments, which work as a hedge, only exist for these shares. Therefore, the structure of the Brazilian market indicates that the differences in herding between the two groupings is small, although the herding is significant and highly persistent.

The maximum likelihood estimates of the parameters are given in Tables 2 and 3. All model (1) coefficients are statistically significant. Parameters associated with herding σmη and ϕm are significant at the 1% level for the two cases. Therefore, there is strong empirical support that both BOLSA and IBOVESPA investors exhibit sentimental herding behaviour, and as expected, we estimated herding coefficients close to AR (1) in BOLSA (0.929) and IBOVESPA (0.872).

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[4]In model (5), we used data from August 2011 to December 2017, due to their availability. Model (5) did not converge for BOLSA.

Analyzing in detail Tables 2 and 3, we conclude that, although BOLSA has higher persistence parameters (ϕ_m), it entails smoother herding than IBOVESPA, proved by its smaller signal-to-noise ratios ($\phi_{mn}/SDln\beta$). Taking Model (1) as an example, we see that the total variability in $SDln\beta_t$ explained by herding is about 3.8% in BOLSA against 10.5% in IBOVESPA. That could be due to the lower liquidity of companies listed in BOLSA and its consequent lower reaction to continuous market movements.

The DY variable, market volatility, and the assetpricing factors SMB and WML were significant for both cases, indicating that herding is significant irrespective of these variables rising or falling. On the other hand, the volatility index (IVOL) and Political Risk, proxies that measure fear, and the interest rate structure do not explain the herd behaviour.

Figure 1 shows the evolution of our measurement of h_{mt} for BOLSA and IBOVESPA. The herding path oscillates between -1.40 and 0.60 for both bases, implying that herding was intense in the period under analysis. If we look in detail at the herding path, it is possible to identify an adverse herding trend in the outbreak of the global financial crisis, followed by an increase in herding between 2009 and the middle of 2016 for both bases. From this moment on, there was an adjustment to the longterm equilibrium of the risk-return relationship from mispricing of IBOVESPA companies as opposed to the continuity of herding in BOLSA companies. Such a result can be partly explained by the economic and political crisis of Brazil from this time on, accentuated by the strong position of institutional investors in IBOVESPA companies.

2.4
Final Discussions

Herding is an important feature of investor behaviour in financial markets. In this work, we adapted the standardized beta of Hwang, Rubesam, and Salmon (2018) and applied it in the state–space model of Hwang and Salmon (2004).

This study investigates the occurrence of herding in the Brazilian stock market between January 2004 and December 2017, for two groupings of companies: the IBOVESPA, comprising the largest companies by capitalisation and BOLSA, comprising the other companies. When we analyze the herding path, we observe that for most of the time the two bases have the same behavior, i.e., an adverse herding trend in the outbreak of the global financial crisis, followed by an increase in herding. However, from 2016 forward, IBOVESPA companies adjusted to the long-term equilibrium of the risk-return relationship from mispricing. Concerning the control variables, we verified that the DY variable, market volatility, SMB and WML factors were significant for both cases, indicating that herding is significant irrespective of those variables behavior.

Table 1.
Descriptive statistics

	Maximum	Minimum	SD	Average
$LN(H_t^*)$_IBOVESPA	4.317	0.530	0.722	1.751
$LN(H_t^*)$_BOLSA	2.444	0.486	0.442	1.242
Market Volatility	-5.609	-16.917	2.099	-9.620
Market Returns	0.078	-0.122	0.029	0.002
SMB	0.069	-0.068	0.020	-0.002
HML	0.063	-0.052	0.019	0.001
WML	0.080	-0.115	0.003	0.024
Ln(Risk)	6.518	3.104	0.568	4.934
DY	5.003	1.645	2.698	0.569
IVOL	34.864	18.161	3.521	23.351
TSIR	3.898	-2.518	1.657	1.068

Table 2.
Kalman's filter results for IBOVESPA

Variables	Model (1) - No exogenous variables	Model (2) - With Excess Return, Volatility	Model (3) - With Excess Return, Volatility, SMB, HML, and WML	Model (4) – With Political Risk and DY	Model (5)- With Ivol and TSIR
μ	1.739^{***}	2.064^{***}	2.005^{***}	0.465^{***}	1.014
σ_{mv}	0.190^{***}	0.188^{***}	0.177^{***}	0.201^{***}	0.269^{***}
ϕ_m	0.872^{***}	0.878^{***}	0.880^{***}	0.903^{***}	0.879^{***}
$\sigma_{m\eta}$	0.076^{***}	0.072^{***}	0.073^{***}	0.054^{***}	0.091^{***}
r_m		1.021	0.854		
$log - VM$		0.034^{*}	0.027		
SMB			-5.341^{*}		
HML			1.057		
WML			-3.359^{*}		
Dy				0.313^{**}	
Risk				0.087	
TSIR					-0.055
Ivol					0.029
Log	-144.811	-143.264	-140.480	-141.481	-74.114
AIC	1.771	1.776	1.779	1.755	2.194
SIC	1.845	1.888	1.946	1.867	2.383
$\sigma_{m\eta}/SDln\beta$	0.105	0.099	0.101	0.074	0.127

Notes: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively AIC: Akaike information criteria; SIC: Schwarz information criteria.

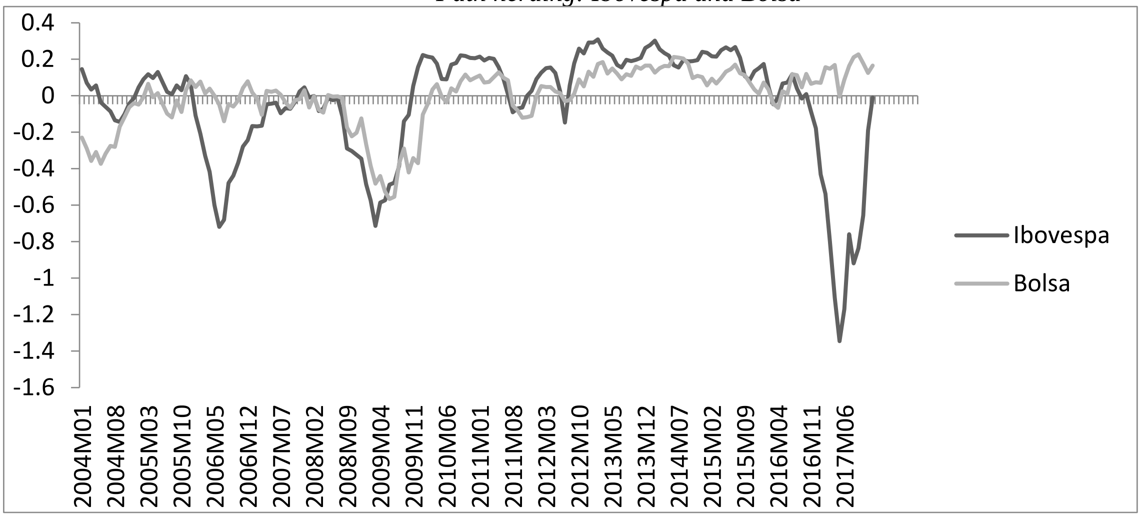
Table 3.
Kalman's filter results for BOLSA

Variables	Model (1) - No exogenous variables	Model (2) - With Excess Return, Volatility	Model (3) - With Excess Return, Volatility, SMB, HML and WML	Model (4) - With Political Risk and DY
μ	1.259^{***}	1.496^{***}	1.457^{***}	0.138^{***}
σ_{mv}	0.080^{***}	0.075^{***}	0.070^{***}	0.085^{***}
ϕ_m	0.929^{***}	0.927^{***}	0.932^{***}	0.957^{***}
$\sigma_{m\eta}$	0.017^{***}	0.016^{***}	0.016^{***}	0.006^{***}
r_m		-1.788^{**}	-1.627^{*}	
$log - VM$		0.024^{**}	0.027^{*}	
SMB			-3.730^{***}	
HML			-0.859	
WML			-2.253^{***}	
Dy				0.270^{***}
Risk				0.077
TSIR				
Ivol				
Log	-60.759	-56.101	-51.927	52.977
AIC	0.770	0.739	0.725	0.702
SIC	0.845	0.850	0.892	0.813
$\sigma_{m\eta}/SDln\beta$	0.038	0.037	0.037	0.014

Notes: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively AIC: Akaike information criteria; SIC: Schwarz information criteria.

Figure 1.

Path herding: Ibovespa and Bolsa



3
Analyzing herding behavior in commodities markets – an empirical approach

3.1
Introduction

In the early 2000s, the commodities market underwent a significant transformation. Many participants – index funding, hedge funds - entered the market in search of the new asset class to diversify their portfolios. This process is called financialization of the commodities markets (Irwin and Sanders, 2012; Cheng and Xiong, 2014). Food commodity prices soared coincidentally in the same period. Etienne, Irwin, and Garcia (2018) point out that some participants blame speculation as the main driver for the food com- modities price spike. Robles, Torero, and Braun (2009) argue that changes in supply and demand are not capable of explaining the increase in the food price itself. So, the authors attribute speculation as responsible for the rise in price and fundamentals change. The question remains, does the new participant's behavior affect the risk–return relationship in the food commodities market and are there differences in herding behavior between the food commodities and our all-commodities database?

The debate on commodity financialization is extensive. However, studies focusing on food commodities herd behavior are scarce. From this, the question arises whether there is a herd effect in commodities, especially in food commodities. This study employs beta herding approach, using the methodology developed by Hwang and Salmon (2004) in a state-space model and a standardized adaptation of Hwang et al. (2018). Our study innovates by including other control variables, such as volatility and market returns, in estimating the herd effect in commodities, along with a standardized beta adaptation model (Hwang et al., 2018).

Empirical studies have discussed whether the financialization process shows a herding pattern. Commodities prices can present a co-movement feature leading to herd behavior (Pindyck and Rotemberg, 1990). It is worth noting that Forbes and Rigobon (2002) showed that correlation coefficients are conditional on market volatility. The authors argued that during the Asian crisis

(1997), Mexican devaluation (1994), and US market crash (1987) unconditional correlation did not increase. Nonetheless, Tang andXiong (2012) found that non-energy commodities become more correlated with oil prices as a result of the financialization process. A massive influx of investment funds and the co-movement across commodities increased in the financial market after 2004. However, Steen and Gjolberg (2013) concluded that the volatile prices were responsible for driving this co-movement after 2008 rather than financialization itself.

A herding is a term in which express the behavior of the investors and fund managers that take a risky position on the market without adequate information (Bikhchandani & Sharma, 2000). Herd behavior is also a pattern in the commodities market, where traders switch position without any economic fundamentals and put in doubt the competitive price model (Pindyck & Rotemberg, 1990). Consequently, investor groups tend to move in the same direction and generate price deviations away from their fundamentals, causing short-term price trends and excess market volatility (Hwang and Salmon, 2004).

The assumption of an efficient market - where all prices reflect the available information - is widely applied in the commodities market to explain whether prices are driven by fundamentals or sentiment (Fama, 1970). Market traders can overreact and push prices away from fundamentals; then rational traders respond to imposing prices to equilibrium. Thus, prices may deviate from supply and demand fundamentals, but only momentary, while commodity markets have a self-correction mechanism (Fishe and Smith, 2018).

The question is, whether the market participants tend to be guided by a trading pattern. Investor groups tend to move in the same direction and generate price deviations away from the fundamentals, causing short-term price trends and excess market volatility (Bikhchandani et al., 1992; Nofsinger and Sias, 1999). In this sense, the study by Gleason et al. (2003), using thirteen commodities in the European market, pointed out that traders operate with their own sets of information, rather than market sentiment, which shows that there is no herd effect in that market. Conversely, the Babalos and Stavroyiannis (2015) study points to a pattern of adverse herd behavior during the global financial crisis.

Several studies empirically analyzed the herding for the stock market. Hwang and Salmon (2004) developed a herd effect measure based on the cross-dispersion of asset sensitivities concerning factors within a market. Hwang and Salmon (2004) apply this approach to herding analysis in the

US and South Korean stock markets and note that market herding presents significant movements and persistence regardless of any market conditions and macroeconomic factors.

Hwang et al. (2018) analyzed the herding in the United States stock market and observed that overconfidence or a sense of optimism causes herding. The authors suggested that individual betas point toward the beta of the market, while insufficient con- fidence or pessimistic sentiment leads to adverse herding, that is, dispersion of the betas of the individual assets relative to the beta of the market. They also analyzed that adverse herding is one of the factors related to low-beta anomaly.

Hwang et al. (2018) argue that estimating herding through the transverse variability of returns presents some methodological pitfalls because it is not indicative of irrational price behavior in the market, as it may only reflect fundamental changes in common factors. Therefore, diverging from the herding estimation approach of Babalos and Stavroyiannis (2015), which uses the transverse variability of returns to the commodity market, we judge appropriate the use of the transverse variability of betas. Thus, we use the model from Hwang and Salmon (2004), already tested in the stock market, and we propose a new measure adapted from the standardized beta of Hwang et al. (2018) for the commodities context, which corrects the heteroscedastic distribution of errors in beta estimation.

We suggest as future research to test the existence of a low-beta anomaly in the commodities markets and whether such anomaly relates to periods when markets show adverse herding behavior, similar to Hwang et al. (2018) findings in the stock markets.

3.2
Methodology

This study investigates the presence of herding in the commodities market between January 2000 and October 2018 for the following commodities: soybeans, sugar, wheat, coffee, corn, cocoa, cotton, live cattle, feeder cattle, orange juice, WTI (Oil), natural gas, coal, copper, and silver. We then extract the food commodities to verify their behavior in isolation.[1] As a market proxy, we use Standard & Poor's Goldman Sachs Commodity Index. We obtained the data from Bloomberg.

In this study, we use the state-space methodology proposed by Hwang and Salmon (2004) and an adaptation of the standardized beta measurement based on Hwang et al. (2018).

According to Hwang and Salmon (2004), when there is a herd effect, the β coefficient must be corrected according to Eq. (1), which empirically extracts sentimental herding, given by h_{mt}:

$$\frac{E_t^b(r_{it})}{E_t^b(r_{mt})} = \beta_{imt}^b = \beta_{imt} - h_{mt}(\beta_{imt} - 1), \tag{1}$$

where $\mathrm{E}_{\mathrm{t}}^{\mathrm{b}}\,(\mathrm{r}_{\mathrm{it}})$ and $\beta_{\mathrm{imt}}^{\mathrm{b}}$ are the short-term conditional biased market expectations regarding excess returns from asset *i* and its beta at time *t*, respectively, and h_{mt} is the latent herd effect parameter that varies with time, with $\mathrm{h}_{\mathrm{mt}} \leq 1$. In general, when $0 < \mathrm{h}_{\mathrm{mt}} < 1$, there is a degree of herd effect, which is determined by the magnitude of h_{mt}.

If there is no herding in equation (1), then $\beta_{imt}^b = \beta_{imt}$. The transverse variation β_{imt}^b, with the logarithmic transformation, is given by:

$$\ln\,[Std(\beta_{imt}^b)] = \ln\,[Std(\beta_{imt}) + \ln(1 + h_{mt})] \tag{2}$$

Rewriting this in state-space model, we get:

$$\ln\,[Std(\beta_{imt}^b)] = \mu_m + \upsilon_{mt}, \tag{3}$$

where μ_m is a short-term constant and $H_{\mathrm{mt}} = \ln\,(1\text{-}h_{mt})$ that follows an AR (1) process. Based on this, two spatial state models can be estimated. Model (1) will be estimated using equation (4):

(Model 1)

$$\ln\,[Std(\beta_{imt}^b)] = \mu_m + H_{mt} + \upsilon_{mt}$$
$$H_{mt} = \phi H_{mt-1} + \eta_{mt}\ , \tag{4}$$

where $\upsilon_{mt} \backsim iid(0, \sigma_{mv}^2)$ and $\eta_{mt} \backsim iid(0, \sigma_{m\eta}^2)$. Equation (4) represents the state-space model based on the Kalman filter method. In this model, the focus will be only on the dynamic structure of the latency variable H_{mt}. When $\sigma_{mn}^2 = 0$, there is no herding, meaning that $H_{mt} = 0$ for all *t*. In this case model 1 becomes:

$$\ln\,(H_t^*) = \mu_m + \upsilon_{mt} \tag{5}$$

If σ_{mn}^2 is statistically significant, there is evidence of herding and a significant ϕ supports this particular autoregressive structure. On restriction is that the herding process should be stationary, implying that $|\phi_m| < 0$ (Hwang and Salmon, 2004).

Model (2) adds market volatility ($\log \sigma_{mt}$) and market returns (r_{mt}), as independent variables, to equation (4).

(Model 2)

$$\ln\left[Std(\beta_{imt}^{b})\right] = \mu_m + H_{mt} + \theta_{c1}\log\sigma_{mt} + \theta_{c2}\mathrm{r}_{mt} + \upsilon_{mt}$$

$$H_{mt} = \phi H_{mt-1} + \eta_{mt} \tag{6}$$

As a second measure of beta herding, we propose the standardized beta, following the methodology used by Hwang, Rubesam, and Salmon (2018):

$$H_t^* = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{\widehat{\beta_{it}^{b}} - \overline{\widehat{\beta}_{it}^{b}}}{\hat{\sigma}_{\widehat{\beta_{it}^{b}}}}\right)^2 = V_{c-norm}(\beta_{imt}^{b}), \tag{7}$$

where $\overline{\hat{\beta}_{it}^{b}}$ is the mean of the betas, n is the number of assets, and $\hat{\sigma}_{\widehat{\beta_{it}^{b}}}$ is the standard error of $\widehat{\beta_{it}^{b}}$ and V_{c-norm} is the Normalised Variance.

Substituting equation (1) into equation (6), and given that the cross sectional mean of β_{imt}^{b} is always 1, we have:

$$H_t^* = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{\beta_{imt} - h_{mt}(\beta_{imt} - 1) - 1}{\hat{\sigma}_{\widehat{\beta_{it}^{b}}}}\right)^2$$

$$H_t^* = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{\beta_{imt} - 1}{\hat{\sigma}_{\widehat{\beta_{it}^{b}}}}\right)^2 (1 - h_{mt})^2$$

$$\ln(H_t^*) = \ln\left[V_{c-norm}(\beta_{imt}^{b})\right] + 2\ln(1 - h_{mt}) \tag{8}$$

From equation (8) we can get:

$$h_{mt} = 1 - \sqrt{exp\,(h_{mt})} \tag{9}$$

Using the same argument as Hwang, Salmon (2004):

$$\ln\left[V_{c-norm}(\beta_{imt}^{b})\right] = \mu_m + \upsilon_{mt} \tag{10}$$

Models (3) and (4) are adaptations of models (1) and (2), using Hwang, Rubesam, and Salmon's (2018) standardized beta measurement.

3.3
Results

The maximum likelihood estimates of the parameters are presented in Tables 1 and 2. All the coefficients of the model (1) are statistically significant. The parameters associated with herding, σ_{mn}, *AND* φ_m *(*the persistent herding parameters) are significant at 1% for the two samples.

Therefore, there is empirical evidence that commodity investors follow sentimental herding. A higher AR coefficient (1) of herding is estimated for the base containing all commodities (0.947) than for the food commodities base (0.783). Analyzing in detail Tables 1 and 2, we conclude that, although the all commodities base have higher persistence parameters (φ_m), it entails smoother herding than the food base, implying in a smaller signal-to-noise ratio ($\sigma_{m\eta}/SDln\beta$). Taking Model (1) as an example, we see that the total variability in $SDln\beta_t$ explained by herding is about 6.4% in food commodities against 0.8% in all commodities. Adjustment in supply and demand can explain the results for the food sample.

When analyzing the control variables, we observe that the market returns coefficient, a proxy of optimism, is positive but not significant, which is similar to the results found in the stock markets (Hwang and Salmon, 2004). In the case of the food base, the market volatility control variable is significant, indicating that herding is significant irrespective of these variables rising or falling.

Table 1

Kalman filter results for food commodities.

Variables	Model (1)-HS (2004) without exogenous variables	Model (2)-HS (2004) with Market Return, Volatility	Model (3)-HS (2018) without exogenous variables	Model (4)-HS (2018) with Market Return, Volatility
μ	-1.184^{***}	-1.495^{***}	0.434^{***}	0.130
σ_{mv}	0.099^{***}	0.099^{***}	0.464^{***}	0.434^{***}
ϕ_m	0.783^{***}	0.731^{***}	0.968^{***}	0.966^{***}
$\sigma_{m\eta}$	0.026^{***}	0.024^{***}	0.007^{***}	0.006^{***}
Market Returns		0.207		0.216
MV		51.009^{**}		52.009^{**}
Log likelihood	-102.946	-98.394	-245.804	-243.928
AIC	0.946	0.923	2.210	2.211
SIC	1.006	1.014	2.271	2.302
$\sigma_{m\eta}/SDln\beta$	0.064	0.060	0.009	0.007

***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. AIC: Akaike information criteria; SIC: Schwarz information criteria. MV = Market Volatility.

Table 2

Results of the Kalman filter for all commodities.

Variables	Model (1)-HS (2004) without exogenous variables	Model (2)-HS (2004) with Market Return, Volatility	Model (3)-HS (2018) without exogenous variables	Model (4)-HS (2018) with Market Return, Volatility
μ	-0.634^{***}	-0.556^{***}	2.333^{***}	2.187^{***}
σ_{mv}	0.035^{***}	0.036^{***}	0.332^{***}	0.327^{***}
ϕ_m	0.947^{***}	0.951^{***}	0.714^{***}	0.704^{***}
$\sigma_{m\eta}$	0.002^{***}	0.001^{***}	0.081^{***}	0.077^{***}
Market Returns		0.033		0.484
MV		-11.920		22.082
Log likelihood	33.887	34.727	-233.165	-230.768
AIC	-0.264	-0.256	2.098	2.114
SIC	-0.203	-0.165	2.159	2.205
$\sigma_{m\eta}/SDln\beta$	0.008	0.006	0.114	0.108

***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. AIC: Akaike information criteria; SIC: Schwarz information criteria.MV = Market Volatility.

Figure. 1.

Herding for the two bases.

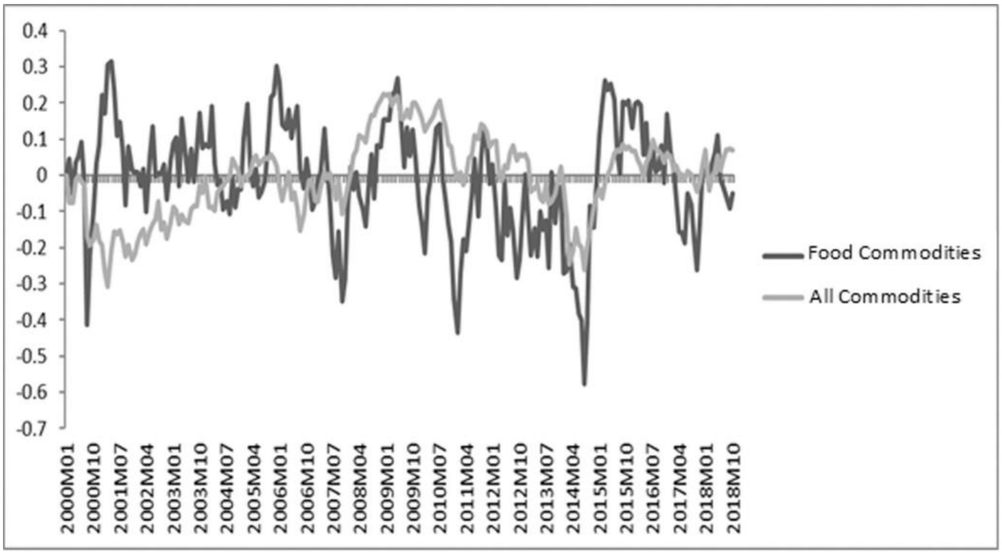


Fig. 1 shows the evolution of h_{mt} for the two bases. The herding path of investors in the food market seems perceptible, with variations between −0.6 and 0.20, implying that herding is intense in the period under analysis, reinforced by the fact that the beta herding coefficient (φ_m) is statistically significant (Tables 1 and 2). We also observe that adverse herding is more intense after we extract the food commodities, suggesting a higher adjustment towards market equilibrium in the long-run related to the risk-return tradeoff of food mispricing (Ai et al., 2006; Adrangi and Chatrath, 2008; Solakoglu and Demir, 2014).

3.4
Final Discussions

Investor reactions could present patterns of behavior that is capable of distorting equilibrium prices in the commodities market and inducing market bubbles (Babalos, Stavroyiannis, and Gupta 2015). This paper contributes to the literature on the herd effect in the food commodities market and innovates by including market volatility and returns in the estimation of the herd effect, using a new empirical approach.

This study uses the Hwang and Salmon (2004) model and the adaptation of the standardized beta measurement based on Hwang et al. (2018) to test the herd effect for 15 commodities and then extracts the food commodities and investigates their effects separately. By using a state-space model, we find evidence of sentimental herding on both bases. Analyzing the control variables, we verified that the market volatility control variable is significant, indicating that herding is significant irrespective of these variables rising or falling.

We observe through the herding path that adverse herding is more intense in the case of food commodities. The results are adherent to the rational storage model. Wright (2011) shows that price can respond to changes in the level of available supply given changes in the stocks. When stocks diminish to a certain level, a supply reduction can cause a price spike. A price too high boost supply, leading to an inventory buildup. Therefore, Fishe and Smith (2018) show this effect can last until inventory holders realize that high prices are away from fundamentals, so they will sell their position and prices will drop. The findings suggest that though prices might deviate from fundamentals momentarily, the market has a self-correcting mechanism that prevents prices from diverging from their equilibrium state. This effect could partially explain the adverse herd effect behavior.

4.
Market Stress and Herding: A New Approach to the Cryptocurrency Market

4.1
Introduction

Cryptocurrencies have received much attention in the last few years. Their rapid growth has been accompanied by an enormous interest in the most diverse fields of knowledge, including agents and researchers in capital markets and finance. The cryptocurrency market reached more than U$200 billion in market value in early 2020[5].

Among the studies about digital currencies, several are dedicated to analyzing the efficiency of the digital currency market and its similarity with other assets. Some findings suggest the cryptocurrencies are more susceptible to speculative bubbles than other currencies (Cheah and Fry, 2015; Katsiampa, 2017). Thus, booms and busts in the cryptocurrency market are not always backed up by fundamentals (Chauhan, Ahmad, Aggarwal, & Chandrad, 2019). In other words, aspects not inherent to the market have a significant influence on asset prices in these cases. Throughout this paper, we analyze if this happens in the cryptocurrency market, with statistical tools related to behavioral finances to assess the herding phenomenon's presence and amplitude concerning these assets.

Herding arises when investors abandon their information and beliefs to imitate their peers instead or follow prevailing market movements (Hwang and Salmon, 2004). It is well established that herding is an important behavioral element in financial markets.

[5] Source: https://coinmarketcap.com/

Despite leading to risk-return distortion of individual assets, herding is still generally considered to be a rational behavior (Hwang, Rubesam, and Salmon, 2018).

We investigate asset returns using the concept of beta herding, which focuses on individual deviations from the beta[6] (risk-return relation) of equilibrium rather than on the herding behavior of market specialists (Lakonishok et al., 1992; Wermers, 1999; Welch, 2000; Sias, 2004; Barber et al., 2009; Choi and Sias, 2009). Beta-herding effects on asset returns can be used in financial markets. Thus, the real betas that balance the risk-return relationship are not known and can result from noisy (Damodaran, 2012). Furthermore, overconfidence and optimism are common psychological phenomena in financial markets (Daniel and Hirshleifer, 2015; Hwang, Rubesam and Salmon, 2018)

While herd behavior has been identified empirically in general financial markets, it has yet to be sufficiently explored in the cryptocurrency market. This study aims to determine whether herding behavior in the cryptocurrency market is a pattern and whether it is associated with market stress. Our research employs a beta-herding approach from Hwang and Salmon (2004) and adapts the standardized-beta methodology from Hwang, Rubesam, and Salmon (2018) to a state-space model. We measure the cross-sectional variations in betas stemming from changes in market-outlook confidence among investors.

Previous studies on cryptocurrencies have analyzed the simple cross-sectional variability of returns using approaches from Christien and Huang (1995) and Chang et al. (2000). These approaches to measure herding may not be indicative of irrational herding; they reflect only fundamental changes in common factors. Our study differs from the literature by using the transversal bias in the betas, referred to as "beta herding." When

[6] In finance, the beta coefficient denotes the sensitivity of an asset's returns in relation to the market as a whole. That is, how much asset returns vary with changes in market returns.

individual betas are biased, it converges to the market beta, regardless of their equilibrium risk-return relation (Hwang, Rubesam, and Salmon, 2018).

We formulate two hypotheses: i) The cryptocurrency market presents herding; ii) The level of herding decreases prior to the emergence of market stress. These hypotheses are in line with Hwang and Salmon (2004), who found that level of herding declines before market stress. This paper innovates by applying beta herding to the cryptocurrency market. To enhance the reliability of our findings, we use control variables such as market return, market volatility, and the volatility index.

To measure herding, we use two different approaches. First, we employ the space-state model from Hwang and Salmon (2004). Second, we adapt the standardized-beta methodology from Hwang, Rubesam, and Salmon (2018) to the state-space model. To our knowledge, neither of these two approaches has previously been used to measure herding in the cryptocurrency market. We found that herding toward the market shows significant movement and persistence independent of market conditions, which are expressed through return volatility and the volatility index. The macro-factors do not help to explain the herding patterns. We also found evidence of herding in both bull and bear markets. We also observed a decreased level of herding prior to the emergence of market stress, which indicates that investors tend to rely on fundamentals instead of general market movements before market stress. Our findings are in line with those of Hwang and Salmon (2004) on the stock market. This similarity suggests that investors have common patterns of behavior across different markets.

4.2
Cryptocurrency Literature in Finance

The cryptocurrency market boom has generated euphoria, intense speculation in the financial market, and much interest in academia. Many works have been published addressing various aspects of the cryptocurrency market, including transaction registry dynamics, its source of value, the effect and need for regulation, the potential to replace traditional means of transaction, and the potential use in illicit trade. However, in this section, we rely on cryptocurrency literature in the field of finance. Our study examines herding behavior in the cryptocurrency market, which has been extensively explored in the stock market. Besides, our investigation relates to the study area that proposes to identify common phenomena between the cryptocurrency market and the general financial market.

The literature credits the origin of cryptocurrency technology to Nakamoto (2008), but Kroll, Davey, and Felten (2013) and Bohme et al. (2015) can provide detailed descriptions of the mining process and the technologies used in the operation of cryptocurrency. Although Corbet et al. (2018) and Liu and Tsyvinski (2018) have shown that traditional factors and assets do not influence cryptocurrencies, many internal phenomena occur similarly to the conventional capital market.

Despite its isolation, the cryptocurrency market shares many features with general financial markets. For instance, Cheah and Fry (2015) and Katsiampa (2017) study the formation of speculative bubbles in this market and argue that bitcoins are purely speculative assets. However, Hayes (2017, 2019) refutes it by formulating an equilibrium model in which the price of the currency is equal to its marginal mining cost. Another strand of the literature investigates the role of cryptocurrency as a hedging instrument, however, the results on this subject are also mixed (Dyhrberg, 2016; Aslanidis, Bariviera, and Martínez-Ibañez, 2019; Kang, Yoon, Bekiros, and Uddin, 2019; Pal, and Mitra, 2019; Smales, 2019).

Although several authors have examined market efficiency, their results are not unanimous on whether the cryptocurrency market is efficient (Urquhart, 2016; Nadarajah, and Chu, 2017; Grobys, and Sapkota, 2019; Kristoufek, and Vosvrda, 2019). We intend to collaborate with this literature, since our paper analyzes whether the herding phenomenon found in financial markets can also be found in the cryptocurrency market, fact indicating that would indicate that the latter is not efficient. In this study we use a more sophisticated approach than those of Bouri, Gupta, and Roubad (2018), Ballis and Drakos (2019), and Vidal-Tomás, Ibáñez, and Farinós (2019), which can be explained and found in the following sections.

4.2.1
Herding Literature

In this section, we detail three crucial contributions to our research: Hwang and Salmon's state-space model (2004), which establishes the concept of beta herding; Hwang, Rubesam, and Salmon's standardized-beta methodology (2018), and the adaption by Raimundo Júnior et al. (2019-A; 2019-B) of the standardized-beta methodology to the state-space model. We also examine the use of the herding model in the cryptocurrency literature, reveal its main gaps, and detail our contributions.

In a pioneering study, Hwang and Salmon (2004) apply the state-space model, which measures herding using the concept of beta herding. The model is based on the transversal dispersion of the sensitivity of factors in a state-space model to market assets. This method detects the presence of herding and whether movements in asset returns are induced by movements in market fundamentals. As Hwang and Salmon (2004) focus on the herd effect from beta variation instead returns, the model removes the effects of idiosyncratic movements from any individual. They argue that this measure has better empirical and theoretical characteristics than previous models with similar aims, thus, it is more reliable. Their study analyzes the stock markets in the United States, the United Kingdom, and South Korea, demonstrating that the herd effect is more likely in regular periods than amid market stress. This suggests that periods of crisis or market stress help the market reestablish equilibrium, indicating that efficient prices can be achieved through market stress.

Hwang, Rubesam, and Salmon (2018) formulate an approach to measure herding. They propose an explanation for the low-beta anomaly by investigating asset returns using the concept of beta herding, which measures the cross-sensitivity of betas through changes in investor sentiment. Overconfidence leads individual betas to converge to market beta; low confidence leads to the dispersion of individual betas to market beta. The convergence and dispersion of betas constitute micro models of irrational and adverse herding, respectively; they lead to transversal distortions in asset returns. Applying the standardized-beta measurement to the US stock market, the authors find that adverse beta management is crucial in asset pricing when the market becomes more uncertain with higher volatility and lower returns. The standardized beta provides information on the accuracy of the beta estimate, making it possible to compare the dynamics of the beta herd in different periods, as it is homoscedastic.

Raimundo Júnior et al. (2019-A) formulate an approach that adapts the standardized beta from Hwang, Rubesam, and Salmon (2018) to the state-space model from Hwang and Salmon (2004). The authors argue that this adaptation provides better empirical and theoretical characteristics than the previous model with similar aims. The study analyzes the Brazilian stock market for two different groups of companies: i) listed on the market index; ii) listed on the stock exchange. The results indicate high herding across the board, with only small differences between the groupings. In line with Hwang and Salmon (2004), this study found that there is a decline in herding before periods of market stress. Raimundo Júnior et al. (2019-B) use the same methodology to analyze herding in the commodities market and find that the market has a herd-effect pattern. However, food-commodity betas tend to revert more quickly to stability between supply and demand, resulting in a steady long-term risk-return factor.

We highlight three main contributions to the literature on herding in the cryptocurrency market. The study made by Bouri, Gupta, and Roubad (2018) that examines the presence of herding behavior in the cryptocurrency market using methods from Chang et al. (2000) and Stavroyiannis and Babalos (2017). They focus on the herd effect through variation in returns. The results point to significant herding behavior that varies over time. Using logistic regression, there are evidences that herding emerges as uncertainty rises. Ballis and Drakos (2019) analyze herding in cryptocurrencies trough the transversal (absolute) standard deviation of return, providing evidence that the dispersion of the up-events market follows market movements at a faster pace compared to down-events. Therefore, cryptocurrencies follow market movements instead of reflecting their fundamentals. Vidal-Tomás, Ibáñez, and Farinós (2019) analyze herding in the cryptocurrency market using the same methodology as Balls and Drake (2019). The study suggests that rational asset-pricing models explain the extreme dispersion of returns. It also finds, however, that herding is present during bear markets, which highlights the inefficiency and risk of cryptocurrencies.

A simple cross-variability of returns—the herding measure used in Bouri, Gupta, and Roubad (2018), Ballis and Drakos (2019), and Vidal-Tomás, Ibáñez, and Farinós (2019)—may not be indicative of irrational herding in the market, as it may simply reflect fundamental changes in common factors.

Our study focuses on the cross-sectional deviation of individual betas. Since Tavares, Caldeira, and Raimundo Junior (2020) have already shown it possible to build betas from the cryptocurrency market index (CRIX). If there is herding, the individual betas are biased (herding) toward the market beta (beta equal 1), regardless of their equilibrium risk-return relation.

When adverse herding occurs, there is an increase in the dispersion of individual betas, which indicates that agents are oriented by market fundamentals. The existence of these behaviors in betas suggests that individual assets are mispriced when equilibrium beliefs are suppressed (Hwang, Rubesam, and Salmon, 2018). Our methodology contours the limitation of previous studies in the cryptocurrency market by detecting the relationship between herding in market stress and macro factors.

4.3
Data and Methodology

We will use the methodology based on the concept of beta herding, which measures the cross-sectional deviation of betas, herding causes the β_{it}[7] to deviate from its true β_{it} (medium long-term beta). Herding is a latent variable, hence not observable, the objective of the methodology is to measure this variable through the state-space model. Table 1[8] summarizes four cases that describe the effects of herding on assets beta. When there is perfect herding, the assets betas converge perfectly towards the market portfolio beta (beta = 1). If there is herding, the assets betas converge partially towards the market portfolio beta. Otherwise, in absence of herding the assets beta is equal to true beta. Moreover, in presence of adverse herding, the assets betas diverge from the market

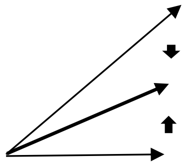
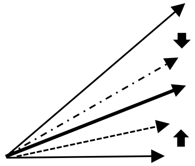
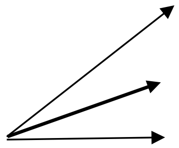
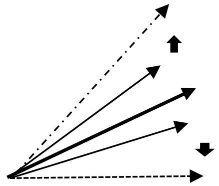
[7] Beta of each cryptocurrency at time t. Therefore, herding influences the betas of all cryptocurrencies at all periods.

[8] The table was built based on Hwang, Rubesam and Salmon (2018).

portfolio beta. Thus, herding leads to distortions in the risk-return relation. We will estimate the betas of cryptocurrencies and then we will use the state-space model to measure herding. The following subsections detail the procedures for betas estimation and formulations to adapt the beta standardized by Hwang, Rubesam and Salmon (2018) in a space-space model. The sections below detail the methodology used, from identification for betas estimation and formulations to adapt the beta standardized beta from Hwang, Rubesam and Salmon (2018) in a space-space model.

Table 1:
Summary of beta herding impacts.

Path Herding	The market presents:	Assets with an true beta greater than 1 presents:	Assets with true beta less than 1 presents:
$h_{mt} > 0$	Herding	Beta < True beta	Beta > True beta
$h_{mt} < 0$	Adverse herding	Beta > True beta	Beta < True beta
$h_{mt} = 1$	Perfect Herding	Beta = 1	Beta = 1
$h_{mt} = 0$	No Herding	Beta = True Beta	Beta = True Beta

	Perfect Herding	Herding	No Herding	Adverse herding
Bias in expected excess returns and betas				

Note: The figure summarizes four cases that describe the effects of investor overconfidence and sentiment on cross-sectional asset prices. Thick solid lines represent the market, the upper and lower thin solid lines represent high and low beta stocks, respectively, and the upper and lower dotted lines represent biases in high and low beta stocks, respectively.

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4.3.1
Data

We collected the prices of the 80 most prominent cryptocurrencies from CoinMarketCap[9] between July 2015 and March 2020. All data were transformed into a log return form. The initial date chosen is the first day that data for at least ten cryptocurrencies is available[10]. For the market return, we used CRIX, which is detailed by Trimborn and Härdle (2018); for the volatility index, we used VCRIX, which is described by Kim, Trimborn, and Härdle (2019).

4.3.2
Estimation of the beta of cryptocurrencies

We estimate betas of CAPM[11] using OLS with rolling window[12] and Newey West robust error; 30 daily observations were used for each beta estimate. To minimize the impact of non-synchronous price movements, we use current and delayed market returns, in line with Lewellen and Nagel (2006), Cederburg and O'Doherty (2016), and Hwang, Rubesam, and Salmon (2018):

$$R_{it} = \alpha_i + \beta_{i,0}^{K3} R_{m,t} + \beta_{i,1}^{K3} R_{m,t-1} + \beta_{i,2}^{K3}\left[(R_{m,t-2} + R_{m,t-3} + R_{m,t-4})/3\right] + \varepsilon_{it} \quad (1)$$

where R_{it} is the excess return on crypto *i* at time *t* and R_{mt} is the excess return on the market (Crix). For each beta ($\beta_i^{K3} = \beta_{i,0}^{K3} + \beta_{i,1}^{K3} + \beta_{i,2}^{K3}$), we calculated the heteroscedasticity-robust standard errors. As a robustness test, we estimate betas using

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9 https://coinmarketcap.com/

10 The date 07/08/2015 was chosen as the initial date of the series, as it is the first day with observations for at least 10 of the considered cryptocurrencies.

11 Capital Asset Pricing Model, for more details see Fama and French (2004).

12 Rolling window is a sample window of fixed size that moves as the estimates advance over time. For example, we set using 30 days of observations, we will use observations from day 1 to day 30 to estimate $\hat{\beta}_{i1}$, then we will use observations from day 2 to day 31 to estimate $\hat{\beta}_{i2}$ and so on.

60-day rolling windows with 60 valid daily observations, referred to as τ_{60}, in line with Fama and French (1992), Baker, Bradley, and Taliaferro (2014), and Hwang, Rubesam, and Salmon (2018). Our main results use K3 with a 30-day rolling window. Unlike Hwang, Rubesam, and Salmon (2018), who use monthly rolling windows, we use daily rolling to account for the short-time horizon of cryptocurrencies.

4.3.3
Herding Measure

When there is a herd effect, according to Hwang and Salmon (2004), the β coefficient must be corrected according to equation (1), which empirically extracts sentimental herding, given by h_{mt}. The herding parameter h_{mt} is assumed to be proportional to the deviations of the accurate beta (β_{imt}) from the market portfolio beta, as follows:

$$\frac{E_t^b(r_{it})}{E_t^b(r_{mt})} = \beta_{imt}^b = \beta_{imt} - h_{mt}(\beta_{imt} - 1), \tag{2}$$

where $E_t^b(r_{it})$ and β_{imt}^b are the short-term conditional biased market expectations regarding excess returns from crypto *i* and beta at time *t*, respectively; h_{mt} is the latent herd effect parameter that varies with time, with $h_{mt} \leq 1$, meaning that the degree of the herd effect is determined by the magnitude of h_{mt}; h_{mt}= 1 suggests perfect herding for the market portfolio, given that all individual cryptocurrency move in the same direction and with the same magnitude as the market portfolio beta (Hwang and Salmon, 2004).

If there is no herding in equation (1), then $\beta_{imt}^b = \beta_{imt}$ and the market is in equilibrium. Since the mean cross-sectional beta of the market portfolio (β_{imt}^b or β_{imt}) is always 1, we have:

$$Std_c\left(\beta_{imt}^b\right) = \sqrt{E_c((}\beta_{imt} - h_{mt}(\beta_{imt} - 1)^2)$$

$$Std_c\left(\beta_{imt}^b\right) = \sqrt{E_c((}\beta_{imt} - 1)^2(1 - h_{mt})$$

$$Std_c(\beta_{imt}^b) = Std_c(\beta_{imt})\,(1 - h_{mt}) \tag{3}$$

4.3.4
The state space model

To extract h_{mt} from $Std_c(\beta_{imt}^b)$, we first take logarithms of equation (3); the transverse variation β_{imt}^b, with the logarithmic transformation, is provided by:

$$\ln\,[Std(\beta_{imt}^b)] = \ln\,[Std(\beta_{imt}) + \ln(1 + h_{mt})] \tag{4}$$

Rewriting this using the state-space model, we arrive at:

$$\ln\,[Std(\beta_{imt}^b)] = \mu_m + \upsilon_{mt}, \tag{5}$$

where μ_m is a short-term constant and H_{mt} = ln(1-h_{mt}), which follows an AR (1) process. Based on this, two space-state models can be estimated. Model (1) is estimated using equation (5):

(Model 1)

$$\ln\,[Std(\beta_{imt}^b)] = \mu_m + H_{mt} + \upsilon_{mt}$$

$$H_{mt} = \phi H_{mt-1} + \eta_{mt}\,, \tag{6}$$

where $\upsilon_{mt} \backsim iid(0, \sigma_{mv}^2)$ and $\eta_{mt} \backsim iid(0, \sigma_{m\eta}^2)$. Equation (7) represents the state-space model based on the Kalman-filter method. In this model, the focus is on the dynamic structure of the latency variable H_{mt}. If $\sigma_{mn}^2 = 0$, there is no herding, meaning that $H_{mt} = 0$ for all *t*. In this case, model (1) becomes:

$$\ln\,(H_t^*) = \mu_m + \upsilon_{mt} \tag{7}$$

If there is evidence of herding, the σ_{mn}^2 is statistically significant, and a significant ϕ supports this particular autoregressive structure. One restriction is that the herding process should be stationary; therefore, H_{mt} should be stationary, as we would not wait for herding toward the market portfolio to be an explosive process, implying that $|\phi_m| < 1$ (Hwang and Salmon, 2004).

We expect $Std(\beta_{imt}^{b})$ to change over time in response to changes in the level of herding in the market, meaning herding promotes the approximation of individual betas to the market beta. However, as discussed by Hwang and Salmon (2004), an essential question about the behavior of the herd extracted from $Std(\beta_{imt}^{b})$ is whether it remains robust in the presence of variables reflecting the state of the market—in this study, market return (Crix), market volatility[13], and the market volatility index (Vcrix). If H_{mt} becomes insignificant upon controlling for these variables, changes in $Std\left(\beta_{imt}^{b}\right)$ can be explained by the control variables rather than by herding (Hwang and Salmon, 2004).

Model (2) adds market volatility ($\log \sigma_{mt}$) and market returns (r_{mt}) as independent variables to equation (7).

(Model 2)

$$\ln\,[Std(\beta_{imt}^{b})] = \mu_m + H_{mt} + \theta_{c1} \log \sigma_{mt} + \theta_{c2} \mathrm{r}_{mt} + \upsilon_{mt}$$

$$H_{mt} = \phi H_{mt-1} + \eta_{mt} \tag{8}$$

Model (3) adds the market volatility index (Vcrix) as an independent variable to equation (8).

(Model 3)

$$\ln\left[Std\left(\beta_{imt}^{b}\right)\right] = \mu_m + H_{mt} + \theta_{c1} \log \sigma_{mt} + \theta_{c2} \mathrm{r}_{mt} + \theta_{c3} \mathrm{Vcrix} + \upsilon_{mt}$$

$$H_{mt} = \phi H_{mt-1} + \eta_{mt} \tag{9}$$

[13] We estimate market volatility as $\log \sigma_{mt}$ with rolling window in line with estimation of the beta of cryptocurrencies, obtaining the same vector size.

We propose using the standardized beta as a second measure of beta herding, as seen in Raimundo Júnior et al. (2019-A; 2019-B), who adapted the standardized-beta methodology to the state-space model.:

$$H_t^* = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{\widehat{\beta_{it}^b} - \overline{\widehat{\beta_{it}^b}}}{\hat{\sigma}_{\widehat{\beta_{it}^b}}}\right)^2 = V_{c-norm}(\beta_{imt}^b), \qquad (10)$$

where $\overline{\hat{\beta}_{it}^b}$ is the mean of the betas, n is the number of cryptocurrencies, $\hat{\sigma}_{\widehat{\beta_{it}^b}}$ is the standard error of $\widehat{\beta_{it}^b}$, and V_{c-norm} is the normalized variance.

Standardizing betas is advantageous because of the problem concerning heteroscedasticity of idiosyncratic errors of market returns. The standardized beta has a homoscedastic distribution and, as a result, is not affected by heteroscedastic behavior in the estimation of the errors. Additionally, we minimize the regression problems noted by Fama and MacBeth (1973) adapting the standardized-beta methodology, as all standardized betas have the same distribution and less extreme values when a small number of changes are omitted (Hwang, Rubesam, and Salmon, 2018).

Substituting equation (2) into equation (10), and provided that the cross-sectional mean of β_{imt}^b is always 1, we have:

$$H_t^* = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{\beta_{imt} - h_{mt}(\beta_{imt} - 1) - 1}{\hat{\sigma}_{\widehat{\beta_{it}^b}}}\right)^2$$

$$H_t^* = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{\beta_{imt} - 1}{\hat{\sigma}_{\widehat{\beta_{it}^b}}}\right)^2 (1 - h_{mt})^2$$

$$\ln(H_t^*) = \ln\left[V_{c-norm}(\beta_{imt}^b)\right] + 2\ln(1 - h_{mt}) \qquad (11)$$

From equation (11), we get:

$$h_{mt} = 1 - \sqrt{exp\,(h_{mt})} \qquad (12)$$

Note that the use of standardized-beta measurement changes the formula of h_{mt}. From the same logic as Hwang and Salmon (2004), we arrive at:

$$\ln\left[V_{c-norm}\left(\beta_{imt}^{b}\right)\right] = \mu_m + \upsilon_{mt} \tag{13}$$

Models (4), (5), and (6) are adaptations of models (1), (2), and (3) that incorporate Hwang, Rubesam, and Salmon's (2018) standardized-beta methodology.

4.3.5
Estimating the cross-sectional standard deviation of the betas

As in Hwang and Salmon (2004), We calculate the standard OLS estimates of the betas using daily data over intervals in the standard market model. After estimating $\hat{\beta}_{imt}^{b}$, we obtain the cross-sectional standard deviation of the cryptocurrencies betas[14] on the market portfolio $\hat{\beta}_{imt}^{b}$ as:

$$Std\left(\hat{\beta}_{imt}^{b}\right) = \sqrt{\frac{\sum_{i=i}^{N_t}(\hat{\beta}_{imt}^{b} - \overline{\hat{\beta}_{imt}^{b}})}{N_t}}$$

where $\overline{\hat{\beta}_{imt}^{b}} = \frac{1}{N_t}\sum_{i=i}^{N_t}\hat{\beta}_{imt}^{b}$ and N_t are the numbers of cryptocurrencies in the period T.

4.4
Results and Discussion

We start presenting results with Table 2 presents some statistical properties of the estimated cross-sectional standard deviations of betas in the market portfolio, following the model from Hwang and Salmon (2004), the standardized-beta methodology from Hwang, Rubesam, and Salmon (2018), and properties of $\ln(H_t\ )$ and $\ln(H_t^{*})$. All beta measurements are highly non-normal, as they are positively skewed and leptokurtic. Beta-

14 We use $Std\left(\hat{\beta}_{imt}^{b}\right)$ as calculated above since $Std\left(\beta_{imt}^{b}\right)$ is not observable (Hwang and Salmon, 2004).

herding measures calculated with $\ln(H_t\ )$ and $\ln(H_t^*)$ are correlated. Therefore, the state-space models proposed in equations (6)– (9) can be legitimately estimated using a Kalman filter. For more details, see Hwang and Salmon (2004).

Table 2:
Statistical Properties.

Statistical Properties

	The cross-sectional standard deviation of OLS beta		The cross-sectional standard deviation of OLS beta	
	Betas on market return-30 days rolling	Standardized-beta herd on the market return-30 days rolling	Betas on market return-60 days rolling	Standardized-beta herd on market return-60 days rolling
Mean	2.619	1.991	1.759	2.251
Standard Deviation	2.218	2.880	1.471	4.613
Skewness	3.054	8.863	3.478	22.223
Excess Kurtosis	15.043	122.075	18.560	691.273
Jarque-Bera Statisics	12558***	99.820***	19644***	321.688***

Spearman Correlation Coefficients

bk3-30 days rolling window	$\ln(H_t)$	$\ln(H_t^*)$
$\ln(H_t)$	1.000	0.358
$\ln(H_t^*)$	0.358	1.000

bk3-60 days rolling window	$\ln(H_t)$	$\ln(H_t^*)$
$\ln(H_t)$	1.000	0.319
$\ln(H_t^*)$	0.319	1.000

Note: Betas are estimated using rolling windows of 30 daily return observations. Current and delayed market returns are used to estimate betas as follows: $R_{it} = \alpha_i + \beta_{i,0}^{K3} R_{m,t} + \beta_{i,1}^{K3} R_{m,t-1} + \beta_{i,2}^{K3}\left[(R_{m,t-2} + R_{m,t-3} + R_{m,t-4})/3\right] + \varepsilon_{it}$. Betas and the robust standard errors of heteroscedasticity are calculated as $\beta_i^{K3} = \beta_{i,0}^{K3} + \beta_{i,1}^{K3} + \beta_{i,2}^{K3}$. We also use rolling windows of 60 daily return observations labeled τ60. The beta-herding measure is calculated by adapting the methodology of Hwang, Rubesam, and Salmon (2018) to the state-space model from Hwang and Salmon (2004). Betas are calculated with the standard errors adjusted by Newey–West's heteroscedasticity. ** represents 5% significance; *** represents 1% significance.

Table 3 shows the results of the state-space model. The ϕ_m coefficient shows the persistence of herding; our hypothesis is to existence of a high coefficient due to the characteristics of the cryptocurrency market, presenting a coefficient close to 1 ($|\phi_m|$ has a restriction of less than 1). The $\sigma_{m\eta}$ the coefficient represents the standard deviation of η_{mt}, this is the coefficient associated with H_{mt}, and for the model to detect the presence of herding, this must be statistically significant. As our hypothesis is to identify herding in the cryptocurrency market, we expect this coefficient to be statistically significant. The signal-to-noise ratio ($\sigma_{m\eta}/\mathrm{SDln}\beta$) presents how much the variability of herding can explain the variability of $Std(\beta_{imt}^{b})$ and H_t^* (see Table 4);); we hypothesize is that the signal-to-noise ratio is high due to market characteristics. When adding control variables to the model, our interest is to verify if H_{mt} becomes insignificant when these variables are included, if this occurs, changes in $Std(\beta_{imt}^{b})$ can be explained by changes in these fundamentals, instead of herding. The structure configured above allows us to take into account the effect of these variables and conditions on them while determining the degree of latent herding behavior through H_{mt}. If herding remains significant even if it includes these variables, these results suggest that herding behavior is significant and exists regardless of the state of the market. Our hypothesis is that herding is significant regardless of the inclusion of the control variables.

The maximum likelihood estimates of the parameters are presented in Table 3 (our main results). We can see that H_{mt} is highly persistent a large ϕ_{m} significant at 1%. We also find that the signal-to-noise ratio ($\sigma_{m\eta}/\mathrm{SDln}\beta$) for models (1) to (3) is not similar to that for models (4) to (7), indicating that the new measurement of beta herding increases the explanatory power of herding in the total variability in H_t^*. In the case of the model (1), which uses the methodology of Hwang and Salmon (2004) without control variables, the herding explains about 3.7% of the variability of $Std(\beta_{imt}^{b})$. In model (4), which uses

Hwang, Rubesam, and Salmon's (2018) standardized-beta methodology, the herding explains about 12.4% of the variability of H_t^*. This increase is more in line with our hypotheses. The estimates of $\sigma_{\mathrm{m}\eta}$ (the standard deviation of η_{mt}) are highly significant in all estimated models; therefore, we conclude that there is a herding for the market portfolio (Crix).

Models (2), (3), (5), and (6) all used control variables. These models showed strong evidence of herding through H_{mt}, controlling for the level of volatility, market return (Crix), and the volatility index (Vcrix), as the $\sigma_{\mathrm{m}\eta}$ (the coefficient) is significantly different from zero and H_{mt} remains highly persistent, indicated by the higher AR coefficient (1). We can see that the market volatility control variable is significant for both models, suggesting that herding is significant irrespective of these variables rising or falling.

It is important to note that the $Std(\beta_{imt}^b)$ and H_t^* decrease as market volatility increases, as the market volatility has a significant negative coefficient. This is in line with the results of Hwang and Salmon (2004). Therefore, before the market becomes riskier, $Std(\beta_{imt}^b)$ and H_t^* decrease. Using the definition of herding proposed by Hwang and Salmon (2004) as an approximation of the individual betas to the market beta—that is, a reduction in the $Std(\beta_{imt}^b)$ and H_t^* due to the H_{mt} process—these results suggest that herding behavior is significant and exists regardless of the state of the market. This suggests that the herding process emerges mainly in times of high volatility or market stress.

Table 3:
Results of the Kalman filter (bk3-30 days)

Variables	Model (1) without exogenous variables	Model (2) with Market Return and Market Volatility	Model (3) with Market Return, Market Volatility, and VCrix	Model (4) without exogenous variables	Model (5) with Market Return and Market Volatility	Model (6) with Market Return, Market Volatility, and VCrix
μ	0.732***	0.287**	0.297**	0.275***	-0.256	-0.262
σ_{mv}	0.002***	0.002***	0.002***	0.035***	0.034***	0.034***
ϕ_m	0.969***	0.962***	0.962***	0.920***	0.903***	0.903***
$\sigma_{m\eta}$	0.023***	0.022***	0.022***	0.106***	0.108***	0.108***
MR		0.127	0.127		0.682	0.684**
MV		-0.173***	-0.169***		-0.200**	-0.203***
VCrix			-0.026			0.037
Log	657.667	665.009	665.271	-854.861	-849.55	-849.476
AIC	-0.791	-0.797	-0.796	1.039	1.035	1.036
SIC	-0.778	-0.778	-0.774	1.052	1.055	1.059
$\sigma_{m\eta}/SDln\beta$	0.037	0.036	0.036	0.124	0.127	0.126

***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. AIC: Akaike information criteria; SIC: Schwarz information criteria.

Table 4:
Results of the Kalman (bk3-60 days)

Variables	Model (1) without exogenous variables	Model (2) with Market Return and Market Volatility	Model (3) with Market Return, Market Volatility, and VCrix	Model (4) without exogenous variables	Model (5) with Market Return and Market Volatility	Model (6) with Market Return, Market Volatility, and VCrix
μ	0.339***	0.062	0.081	0.306	0.137	0.185
σ_{mv}	0.001***	0.001***	0.001***	0.020***	0.020***	0.020***
ϕ_m	0.985***	0.923***	0.983***	0.972***	0.970***	0.970***
$\sigma_{m\eta}$	0.010***	0.010***	0.010***	0.047***	0.047***	0.047***
MV		-0.080	-0.080		0.319	0.307
MR		-0.108***	-0.101***		-0.064	-0.046
VCrix			-0.035			-0.132**
Log	1419.517	1425.879	1427.119	-261.030	-260.001	-258.103
AIC	-1.744	-1.750	-1.750	0.327	0.328	0.327
SIC	-1.731	-1.730	-1.727	0.340	0.348	0.350
$\sigma_{m\eta}$/SDlnβ	0.017	0.017	0.017	0.048	0.051	0.051

***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. AIC: Akaike information criteria; SIC: Schwarz information criteria.

Figure 1 shows the herding path, the value of $\mathrm{h_{mt}}$ throughout the series. When $\mathrm{h_{mt}}$ is positive, it indicates that there is a degree of herding for the market portfolio, which promotes a convergence of assets beta towards the market portfolio beta (see table 1). On the other hand, when there is adverse herding, therefore negative $\mathrm{h_{mt}}$, the assets betas are diverging from the market portfolio beta. Thus, considering that the market portfolio beta is 1, if an asset has a true beta greater than 1 (higher than the market portfolio beta). For example, if the true beta is 1.5, the asset will have a beta less than 1.5 in periods of herding (positive $\mathrm{h_{mt}}$) and greater betas than 1.5 in periods of adverse herding (negative $\mathrm{h_{mt}}$). If an asset has a true beta less than 1 (market portfolio beta), for example, beta 0.8, the directions of the asset beta will be the opposite of the beta greater than 1. If herding exists, the asset will have a beta higher than 0.8, converging towards the market portfolio. When there is adverse herding, it will have a beta less than 0.8, diverging from the market portfolio. The beta adverse phenomenon denotes a "flight to fundamentals," meaning that agents adjust their risk-return relation in the long-run, leading to the average-beta to true beta. Since the divergence among the assets beta and the market portfolio beta will adjust the former in the medium to long term; therefore, adjusting the risk-return relation of this asset. The path herding can explain the low beta anomaly. Notably, a the market that presents the herding adverse phenomenon ($\mathrm{h_{mt}}$ < 1) can lead a beta asset to a lower beta, which we call a low beta anomaly. Thus, this phenomenon can elucidate the low-beta anomaly in specific periods and specify the distortions of the risk-return relation in particular assets.

Figure 1 shows the evolution of the herding measurement ($\mathrm{h_{mt}} = 1 - e^{\mathrm{H_{mt}}}$) using Hwang and Salmon's (2004) methodology for the 80 cryptocurrencies concerning the market return (Crix). This is calculated with betas according to equation (1), following the methodologies of Cederburg and O 'Doherty (2016), Hwang, Rubesam, and Salmon

(2018), and Trimborn and Härdle (2018). It uses bk3 with a 30-day rolling window (Model (1) – Table 1). The herding path of cryptocurrency investors seems perceptible, with variations between 0.8 and -7, implying that herding was intense during the period under analysis; this is reinforced by the fact that the beta-herding coefficient (ϕ_m) is statistically significant. We can see that there are several peaks of adverse herding (h_{mt} negative) where investors tend to adjust to market fundamentals, meaning there is an increase in the dispersion of individual betas relative to the market beta. There is also a clear high peak in 2019, which can be explained by the increase in market returns and the decrease in volatility that year. The figure shows that h_{mt} generally increased before market stress. Similar path-herding behaviors were found by Hwang and Salmon (2004) in the stock market, though with less intensity. This makes sense, given the high volatility of the cryptocurrency market.

Figure 2 shows the evolution of the herding measurement when adapting Hwang, Rubesam, and Salmon's (2018) standardized-beta measurement ($h_{mt} = 1 - \sqrt{e^{H_{mt}}}$) and using bk3 with a 30-day rolling window (Model (4) – Table 1). We can see a decline in path herding with this new measure. The behavior is similar to that shown in Figure 1, which gives robustness to our findings. The path herding using with 60-day rolling windows using the model proposed by Hwang and Salmon (2004) and the adaptation of the standardized-beta measurement are presented as robustness tests in Figure 3 and Figure 4, respectively. These the base-model findings—herding increased before a crisis, but closer inspection reveals that the herd begins to decline prior to the actual onset of the crisis.

Our main results are in line with the findings by Ballis and Drakos (2019). However, we diverge from Bouri, Gupta, and Roubad (2018) and Vidal-Tomás, Ibáñez, and Farinós (2019), as we detected the significant presence of herding, not just in the bear market, which leads to further evidence of the existence of herding in the cryptocurrency market. We use a more sophisticated methodology and this one provides results that fit more into our hypothesis. This paper was the first include control variables and herding analysis so far, so there is no way to compare these findings with previous studies.

Table 5

Regression of Beta Herd Measure on Macro-Variables.

	Model 1	Model 2	Model 3	Model 4
Const	0.642	0.239	0.530	0.261
Market Volatility	0.320***	0.234***	0.281***	0.314***
Market Return	1.880***	0.237	0.908***	-0.023
Vcrix	-0.156	-0.091	0.097	-0.171
Ajust R-Square	0.163	0.028	0.105	0.024

Note: Beta herd measurements (h_{mt}) are regressed with robust standard error (Newey-West) with market volatility, the volatility index, market return. *** means significant at the 1% level, ** significant at the 5% level, * significant at the 10% level. Model 1 represents model 1 from table 3 (using β^{K3}-30 Days), model 2 represents model 4 from table 3 (using β^{K3}-30 Days), model 3 represents model 1 from table 4 (using β^{K3}- 60 Days), model 4 represents model 4 from table 4 (using β^{K3}- 60 Days).

Table 6
The average of the herding measure (h_{mt}) for the differents days.

	Model 1	Model 2	Model 3	Model 4
$\overline{h_{mt\ 20\ days}}$	0.16	0.533	0.241	0.629
$\overline{h_{mt\ 50\ days}}$	0.016	0.518	0.166	0.698
$\overline{h_{mt\ whole\ sample}}$	-0.231	-0.367	0.188	0.148

Note: The average of the herding measure (h_{mt}) for the 20 days with the highest volatility, 50 days with the highest volatility and for the whole sample. Model 1 represents model 1 from table 3 (using β^{K3}-30 Days), model 2 represents model 4 from table 3 (using β^{K3}-30 Days), model 3 represents model 1 from table 4 (using β^{K3}-60 Days), model 4 represents model 4 from table 4 (using β^{K3}- 60 Days).

Table 7
Correlation matrix and herding measures and variables.

	Market Return	Market Volatility	Vcrix
Model 1	-0.199	0.345	0.012
Model 2	0.024	0.171	0.008
Model 3	-0.088	0.307	0.027
Model 4	0.006	0.154	0.005

Note: Correlation matrix between the herding measures and the variables of market return, the volatility index and market return. Model 1 represents model 1 from table 3 (using β^{K3}- 30 Days), model 2 represents model 4 from table 3 (using β^{K3}-30 Days), model 3 represents model 1 from table 4 (using β^{K3}- 60 Days), model 4 represents model 4 from table 4 (using β^{K3}-30 Days).

Figure. 1.
Path herding (HS04) BK-30 days.

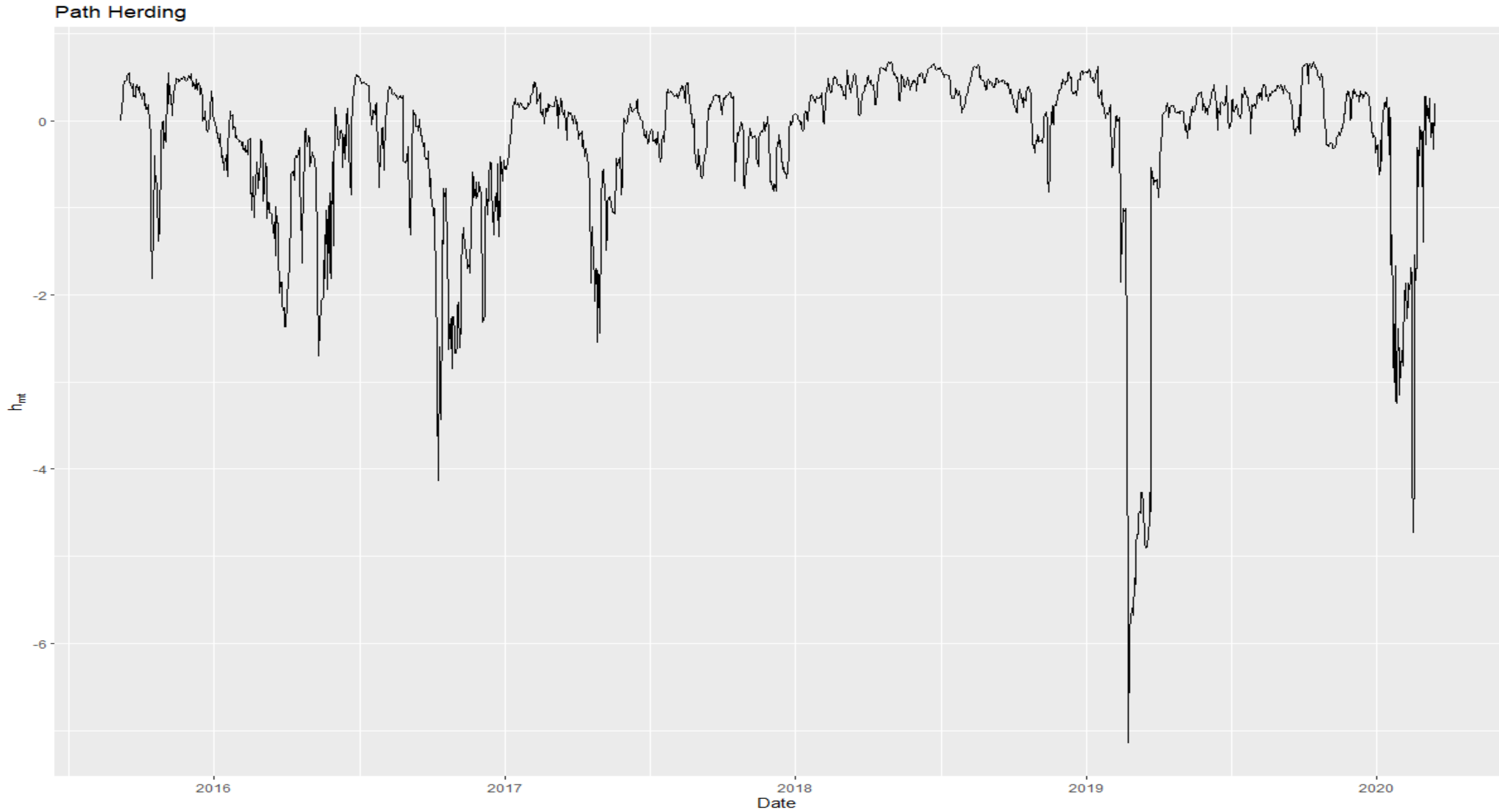

Figure 2.
Path herding (HS18) BK-30 days.

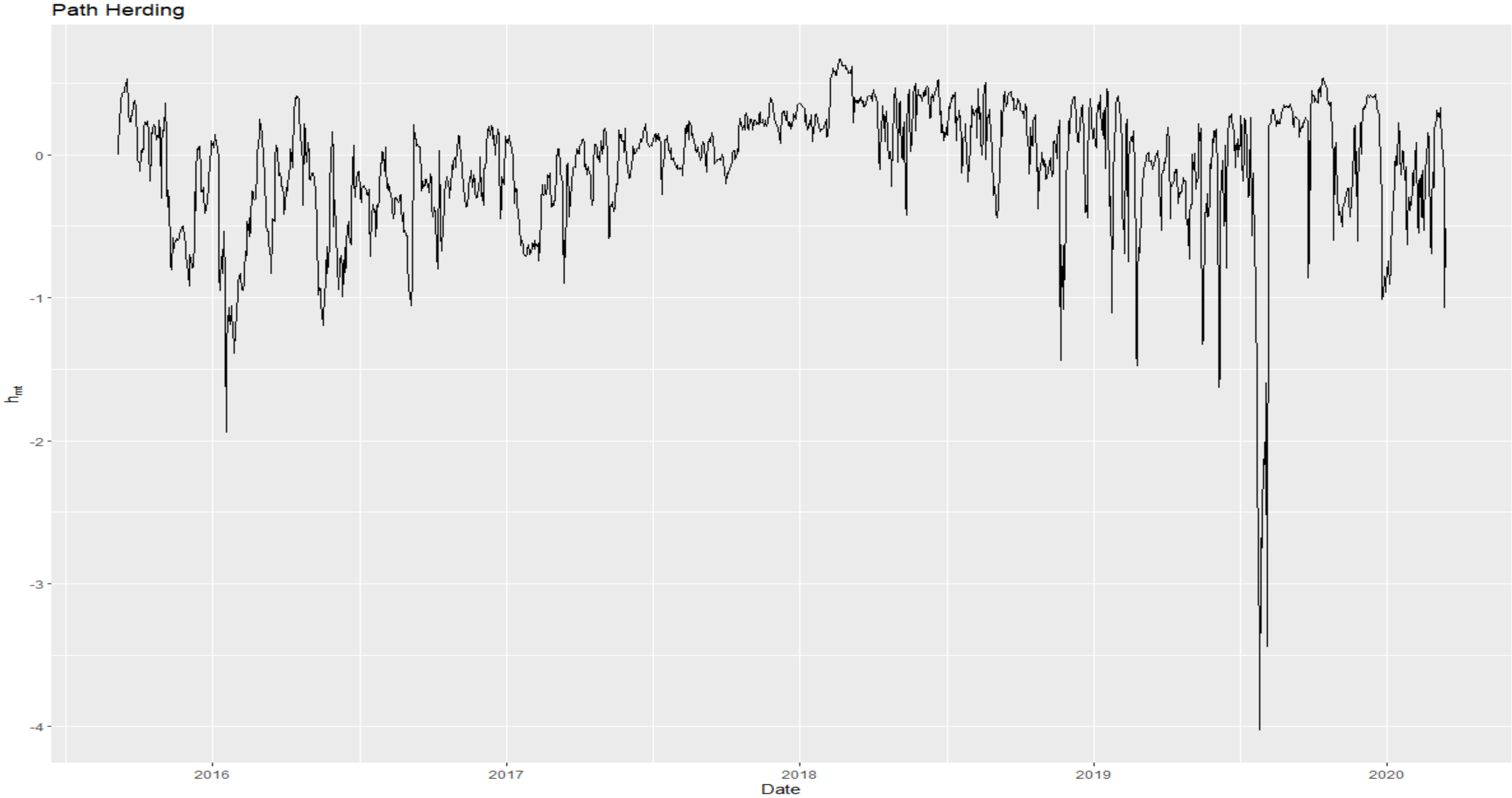

Figure. 3.
Path herding (HS04) BK-60 days.

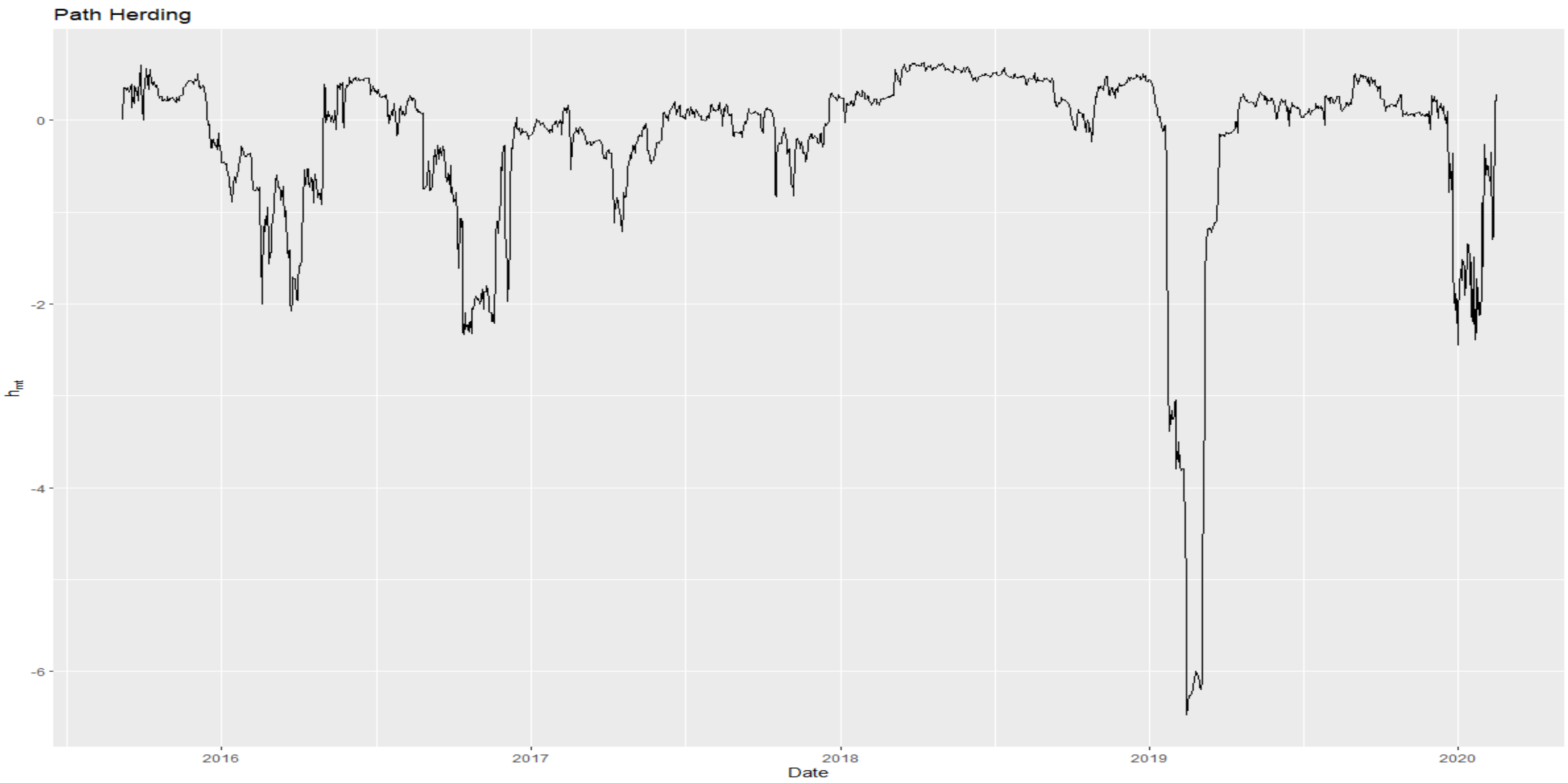

Figure. 4.
Path herding (HS18) BK-60 days.

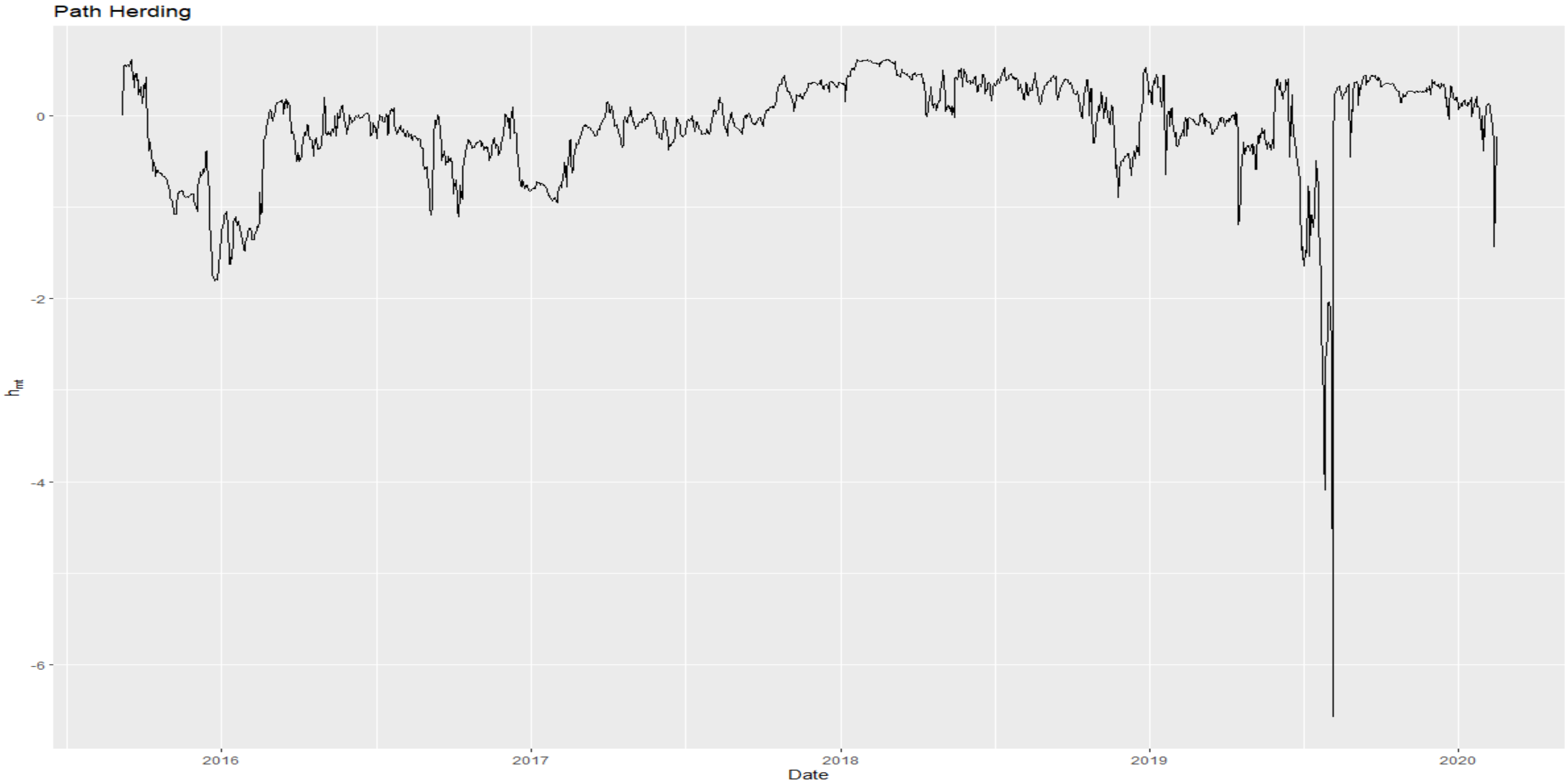

Fig.

4.5
Final Discussions

Herding is an essential feature of investment behavior in financial markets, especially amid market stress. Hwang and Salmon (2004) previously detected a relationship between herding and market stress in the stock market. Although herding behavior has been empirically explored in general financial markets, it has received little attention in the cryptocurrency market. We apply the state-space model from Hwang and Salmon (2004) and adapt to it the standardized-beta methodology from Hwang, Rubesam, and Salmon (2018). Our study differs from the literature, as it uses the transversal bias in the betas known as "beta herding."

Beta herding, as we propose, measures the market-wide cross-sectional dispersion in betas. therefore, herding causes the β_{it} to deviate from its true β_{it}. Herding leads to low betas (betas < 1) being to upward-biased and high betas (betas > 1) being to downward-biased. Thus, cryptocurrencies are more likely to track market movements, rather than those suggested by the equilibrium risk-return relation (Hwang, Rubesam and Salmon, 2018). When adverse herding occurs, the movement is the opposite. The existence of herding and adverse herding indicates that individual assets are mispriced when equilibrium beliefs are suppressed (Hwang, Rubesam, and Salmon, 2018), this movement is summarized in table 1. As herding is a latent variable, therefore not observable, the objective of the study is to identify and measure this variable using the state-space model.

Results revealed that herding toward the market shows significant movement and persistence independent of the market conditions, expressed through market return and the volatility index. Analyzing the path herding, we found that there is adverse herding prior to market stress, suggesting that herding could potentially be used as a predictor of market stress.

The methodology used in this study avoids the limitations of previous studies in cryptocurrency on this topic. The primary outcome of this study is that herding can lead to significant mispricing; in other words, high-intensity herding can lead to market inefficiency. It is worth highlighting that herding declines prior to crises; it represents a flight to fundamentals (Hwang and Salmon, 2004).

Our study identifies whether there is a herding in the cryptocurrency market. Observing this anomaly, one can notice that it has two practical implications. The first one is that herding causes a distortion in the risk-return relation, which leads to cryptocurrency prices and returns imbalance, the reason why the market becomes inefficient. This phenomenon increases the possibility of systematic risks, which compromises market stability. The other implication is in the portfolio selection area. Portfolios can be based on herding, creating value from betas' distortions, or flight to fundamentals. Besides, using herding can be a good predictor for market stress, which can change agents' strategies.

We suggest that future research on this subject examine the presence of a beta-low anomaly in the cryptocurrency market and determine whether herding can explain the anomaly in the market. Additionally, it could investigate whether it is possible to use herding as a predictor of market stress.

5
Conclusion

This thesis elaborates on important issue about herding. To identify this anomaly, we used the herding measurement methods of Hwang and Salmon (2004) and a beta adaptation standardized by Hwang, Rubesam and Salmon (2018) in a space-space model. The herding literature is still small and the thesis aims to collaborate, presenting a new method of measuring herding and analyzing herding in different markets: Brazilian stock market, commodity market and cryptocurrency market.

The use of the model by Hwang and Salmon (2004) has some advantages. First, it allows us to explicitly separate the effect of investors' reactions to herd fundamentals due to market sentiment. Second, the specification of the model as a state-space model provides an estimate of the dynamic evolution of the herding, which allows us to identify the exact periods when herdinh (or anti-herding) behavior is present. The use of a second methodology that standardizes the beta is due to the problem of heteroscedasticity of idiosyncratic errors of market returns. The standardized beta has a homoscedastic distribution and, as a result, is not affected by heteroscedastic behavior in estimating errors.

The first subject studies the occurrence of herding in the Brazilian stock market, in two groups of companies: the IBOVESPA, composed of the companies that make up the Ibovespa index (Brazilian stock market index), and the BOLSA, composed of all the companies on the Stock Exchange of Brazil. Analyzing the herding trajectory, we observe that most of the time, the two groups have the same behavior, that is, an adverse herd trend at the outbreak of the global financial crisis, followed by an increase in the herding. This pattern was also observed in Hwang and Salmon (2004). However, as of 2016, IBOVESPA companies have adjusted to the long-term balance of the risk-return ratio of mispricing, and the Bolsa has not the same pattern.

The second subject studies the literature on the herd effect in the food commodity market and innovates by including volatility and market returns and estimating the herd effect, using a new empirical approach. We used the model by

Hwang and Salmon (2004) and adapted the standardized beta measure based on Hwang et. (2018) to test the herd-to effect in two different databases: the first base consists of 15 commodities and the second base only consists of food commodities. We found evidence of herding on both bases. We observed through the herding path that the adverse of herding is more intense in the case of food commodities. Which is in line with the rational storage model. Wright (2011) shows that price can respond to changes in the level of availability given as changes in inventories. The results suggest that, although prices may momentarily deviate from fundamentals, the market has a self-correcting mechanism that prevents prices from splitting their equilibrium state. This effect may explain her adverse behavior.

The third theme studies to identify if there is herding in the cryptocurrency market. We identified in this study the presence of herding, and a very intense presence of the adverse herding. By identifying the presence of this anomaly in the cryptocurrency market as two practices, herding has implications. The first herding causes a distortion in the risk-return ratio, which drives cryptocurrencies to prices, which is why the price becomes more efficient. This phenomenon increases the possibility of systematic risks, which compromises market stability. The second practical implication lies in the area of portfolio selection. How portfolios can turn into herding, creating from beta distortions or breakout to fundamentals. In addition, the use of man can be a good predictor of market stress, which can change agents' strategies.

6
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