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Jin H. Jung
Head of Trading Research
jjung@prestolabs.io

Summary

- We explore the potential of using funding rates in perpetual futures contracts to predict future price changes.
- Funding rate changes initially account for 12.5% of the variation in price changes over a 7-day period.
- The predictive power diminishes for subsequent periods, indicating limited reliability for single asset predictions.
- Funding rate data may be more useful when applied cross-sectionally across multiple assets.
- A statistical arbitrage alpha using funding rate data shows favorable performance metrics but requires refinement to reduce its turnover.

Introduction

The cryptocurrency market, characterized by its volatility and rapid price fluctuations, has seen the rise of various financial instruments designed to capitalize on these dynamics. Among these, perpetual futures contracts have gained significant traction, allowing traders to speculate on the future prices of digital assets without an expiration date. Central to the functioning of these contracts is the funding rate—a periodic payment mechanism intended to keep the perpetual futures price in line with the underlying spot price. We address the intriguing question: Can the funding rate of perpetual futures be used to predict future price changes?

At its core, the funding rate is designed to correct imbalances between the futures price and the spot price. When the perpetual futures price diverges from the spot price, the funding rate incentivizes traders to take positions that push the futures price back towards the spot price. This self-correcting mechanism reflects market sentiment and positions of traders, offering a potential window into future price movements. Traders often scrutinize the funding rate, considering whether it can serve as a reliable indicator of market direction.

This article explores the predictive power of the funding rate in the context of perpetual futures contracts. We will analyze historical data to identify patterns and correlations, and consider the practical implications for traders. By the end of this exploration, we aim to provide a comprehensive understanding of whether the funding rate can indeed offer foresight into future price changes, enhancing trading strategies in the highly competitive cryptocurrency markets.

For details regarding the perpetual futures and the funding rate, please refer to:
Crypto Derivatives Series I: Futures
Optimizing Funding Fee Arbitrage

Funding Rate vs Price on BTC

Figure 1 illustrates the relationship between annualized funding rate changes and price changes over a one-week period in the context of perpetual futures contracts over time. The period of early 2021 shows that both funding rate changes and price changes are highly volatile. From mid-2021 onwards, the fluctuations in funding rate changes and price changes become less extreme. However, there are still occasional spikes in both metrics. In mid-2023 and early 2024, volatility in funding rate changes and price changes increases noticeably again. The observed patterns suggest a general correlation between significant changes in funding rates and corresponding price changes, highlighting the dynamic nature of the market.

Figure 1. One Week Funding Rate Change and Price Change Time Series

Source: Binance, Presto Research

The scatter plot in Figure 2 depicts the relationship between the 7-day change in annualized funding rate and the 7-day percentage change in price for perpetual futures. Each orange dot on the scatter plot corresponds to a specific 7-day period. The fitted line in the scatter plot indicates a positive correlation, implying that increases in funding rate changes are generally associated with increases in price changes. However, the scatter of points indicates significant variability around this trend.

The R-squared value of 12.5% indicates that changes in the funding rate explain 12.5% of the variability in price changes. The extremely low p-value of 1.91e-115 for the F-statistic indicates that the model is statistically significant, meaning that the relationship observed is highly unlikely to be due to random chance.

Figure 2. Funding Rate Change vs Price Change Scatter Plot

Source: Binance, Presto Research

Table 1. OLS Statistics on Funding Rate and Price Changes

OLS Regression Results

Dep. Variable:	y	**R-squared:**	0.125
Model:	OLS	**Adj. R-squared:**	0.125
Method:	Least Squares	**F-statistic:**	558.2
Date:	Mon, 29 Jul 2024	**Prob (F-statistic):**	1.91e-115
Time:	14:22:20	**Log-Likelihood:**	4279.6
No. Observations:	3895	**AIC:**	-8555.
Df Residuals:	3893	**BIC:**	-8543.
Df Model:	1		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Funding Rate Change	0.1247	0.005	23.627	0.000	0.114	0.135
Intercept	0.0080	0.001	6.199	0.000	0.005	0.011

Omnibus:	198.227	**Durbin-Watson:**	0.214
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	565.921
Skew:	0.234	**Prob(JB):**	1.29e-123
Kurtosis:	4.808	**Cond. No.**	4.08

To see whether funding rate changes have prediction power over price changes, we need to compare the funding rate change of the current interval with the price change of the next interval. The scatter plot, Figure 3, depicts the relationship between the funding rate change at time T and the subsequent price change at time T+1. The fitted line indicates a near-zero correlation. The zero R-squared and the large p-value imply that the model has no prediction power. Given this result, price changes for a single asset cannot be reliably predicted using only funding rate changes.

Figure 3. Funding Rate Change at T vs Price Change at T+1 Scatter Plot

Source: Binance, Presto Research

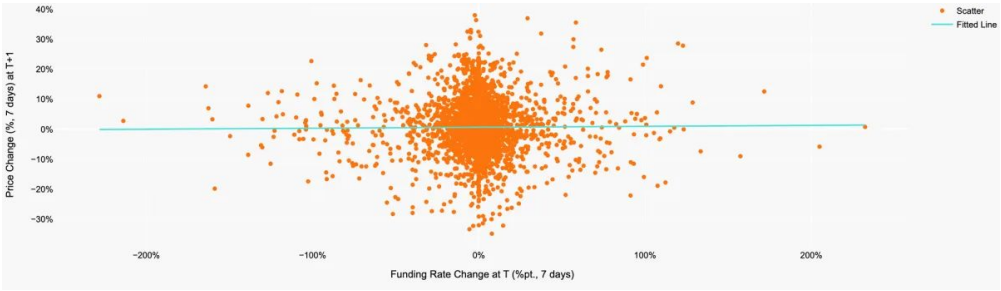

Table 2. OLS Statistics on Funding Rate Change at T and Price Change at T+1

OLS Regression Results

Dep. Variable:	y	**R-squared:**	0.000
Model:	OLS	**Adj. R-squared:**	-0.000
Method:	Least Squares	**F-statistic:**	0.3219
Date:	Tue, 30 Jul 2024	**Prob (F-statistic):**	0.570
Time:	13:39:37	**Log-Likelihood:**	4042.4
No. Observations:	3874	**AIC:**	-8081.
Df Residuals:	3872	**BIC:**	-8068.
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Funding Rate Change	0.0032	0.006	0.567	0.570	-0.008	0.014
Intercept	0.0066	0.001	4.848	0.000	0.004	0.009

Omnibus:	168.032	**Durbin-Watson:**	0.096
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	475.975
Skew:	0.170	**Prob(JB):**	4.40e-104
Kurtosis:	4.683	**Cond. No.**	4.07

A Statistical Arbitrage Alpha Using Funding Rate

While the predictive power of funding rate changes for price movements may appear limited, it doesn't imply that the data lacks usability for trading. Predicting the price change of a single asset using funding rate changes might be challenging. However, the data could be useful if applied cross-sectionally over a universe of multiple assets for predicting relative price movements. A simple statistical arbitrage alpha, formulated as follows:

```
alpha := scale(indneutralize(decay_linear(funding_rate, 24) -
decay_linear(funding_rate, 6), IndClass.universe), 2e6)
```

is evaluated on the top 50 liquid universe on Binance USDⓈ-M with 5-minute interval data, not considering any transaction cost. The functions used in the formula are well described in [1]. The result is illustrated in Figure 4 and Table 3.

Figure 4. PNL Plot of the Simple Alpha Using Funding Rate

Source: Presto Research

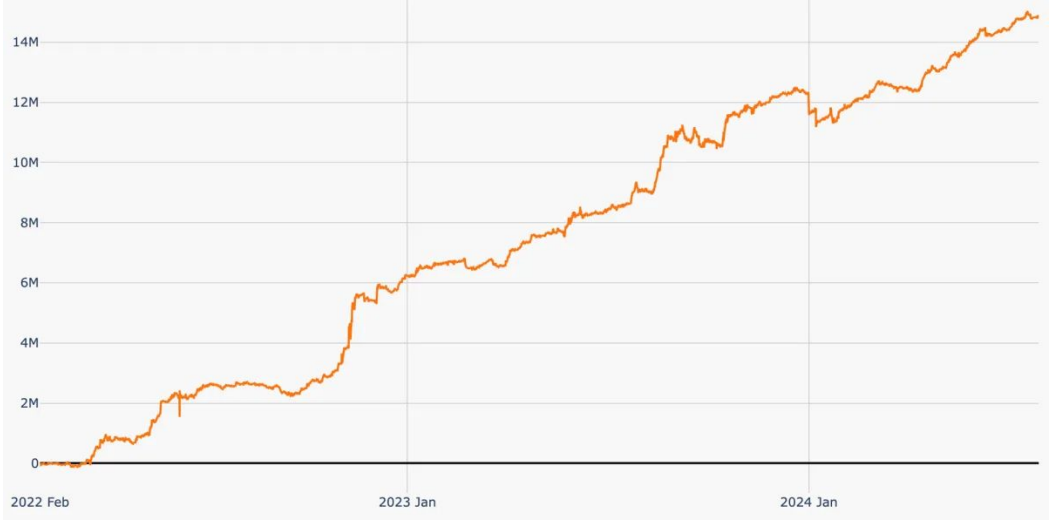

Table 3. Stats of the Simple Alpha Using Funding Rate
(Return, Sharpe, Sortino and Return/MDD are annualized)

Funding_Rate_Alpha

	GMV	Return (%)	Sharpe	Sortino	Return/MDD	MDD (%)	Daily Win Ratio (%)	Daily Turnover (%)	Return/Trade (bp)
20220201-20220301	2.00E+06	-44.78	-2.11	-3.33	-9.55	4.69	46.43	3181.63	-0.39
20220301-20220401	2.00E+06	529.04	8.78	14.52	52.13	10.15	58.06	2998.00	4.83
20220401-20220501	2.00E+06	34.47	0.76	1.15	2.15	16.00	50.00	3233.06	0.29
20220501-20220601	2.00E+06	795.92	12.95	22.98	132.31	6.02	74.19	3355.00	6.50
20220601-20220701	2.00E+06	189.81	1.66	2.50	4.64	40.87	60.00	3267.71	1.59
20220701-20220801	2.00E+06	65.70	2.03	3.47	6.50	10.11	48.39	3351.54	0.54
20220801-20220901	2.00E+06	-99.77	-3.48	-5.25	-7.65	13.04	38.71	3131.19	-0.87
20220901-20221001	2.00E+06	16.11	0.34	0.52	0.86	18.75	56.67	3208.46	0.14
20221001-20221101	2.00E+06	481.34	9.75	18.00	92.39	5.21	74.19	3521.61	3.74
20221101-20221201	2.00E+06	1278.53	9.17	14.99	47.23	27.07	70.00	3458.93	10.13
20221201-20230101	2.00E+06	478.06	6.56	11.13	32.68	14.63	54.84	3223.45	4.06
20230101-20230201	2.00E+06	221.15	3.95	6.37	27.21	8.13	58.06	3050.44	1.99
20230201-20230301	2.00E+06	-117.29	-2.73	-4.31	-6.20	18.93	53.57	3380.53	-0.95
20230301-20230401	2.00E+06	137.73	3.21	4.82	9.80	14.06	74.19	3310.07	1.14
20230401-20230501	2.00E+06	546.81	11.76	19.85	109.03	5.02	66.67	3334.51	4.49
20230501-20230601	2.00E+06	400.72	5.50	8.76	26.16	15.32	58.06	3343.54	3.28
20230601-20230701	1.99E+06	83.27	1.23	1.75	4.20	19.84	66.67	3592.45	0.64
20230701-20230801	2.00E+06	367.70	6.13	9.94	21.17	17.36	58.06	3219.80	3.13
20230801-20230901	2.00E+06	1020.58	12.58	21.83	90.71	11.25	64.52	2956.84	9.46
20230901-20231001	2.00E+06	-23.77	-0.23	-0.36	-0.65	36.39	53.33	3075.35	-0.21
20231001-20231101	2.00E+06	564.36	5.96	8.65	32.42	17.41	48.39	3812.35	4.06
20231101-20231201	2.00E+06	292.48	3.83	5.78	17.03	17.18	66.67	4093.20	1.96
20231201-20240101	2.00E+06	-120.27	-2.37	-3.26	-4.19	28.68	58.06	3893.75	-0.85
20240101-20240201	1.99E+06	-118.20	-1.22	-1.70	-2.97	39.79	64.52	3939.49	-0.82
20240201-20240301	2.00E+06	454.63	8.73	14.10	56.96	7.98	75.86	4122.06	3.02
20240301-20240401	2.00E+06	-29.36	-0.69	-1.12	-1.49	19.70	45.16	4045.84	-0.20
20240401-20240501	2.00E+06	419.06	8.49	14.02	37.02	11.32	70.00	3778.25	3.04
20240501-20240601	2.00E+06	579.50	12.42	20.09	54.70	10.59	83.87	3897.51	4.07
20240601-20240701	2.00E+06	193.27	4.32	6.55	12.26	15.76	60.00	4053.24	1.31
20240701-20240706	2.00E+06	882.19	24.39	42.47	454.28	1.94	100.00	3889.18	6.21
Total	2.00E+06	302.87	4.50	6.98	4.66	64.95	60.20	3479.08	2.39

The statistics, such as annualized return and Sharpe ratio, appear highly favorable; however, the daily turnover is extremely high for inclusion in a statistical arbitrage strategy. Despite this, the alpha can be further refined to lower the turnover while reasonably preserving the overall performance statistics.

Conclusion

This analysis investigates whether the funding rate of perpetual futures can predict future price changes. Initial findings suggest a statistically significant yet weak correlation between funding rate changes and price movements, with funding rate changes explaining 12.5% of price variation over a 7-day period. However, the predictive power diminishes significantly when looking at subsequent periods, implying limited reliability for single asset predictions. Despite this, funding rate data can still be valuable in strategies targeting multiple assets for predicting relative price movements, as demonstrated by a statistical arbitrage alpha that shows promising performance metrics, albeit with high turnover. Further refinement of this alpha could reduce turnover while maintaining its performance.

References

[1] Z. Kakushadze, “101 Formulaic Alphas.” arXiv, Mar. 18, 2016. Available: http://arxiv.org/abs/1601.00991

About Presto

Preso Labs is a quantitative trading firm, established in Singapore in 2014. We are a team of competition-winning researchers, engineers and finance professionals who enjoy solving most challenging real-world problems in finance. Trading around $3 billion daily, we are one of the most active cryptocurrency traders globally. We provide liquidity provisioning and OTC execution services to blockchain projects, in addition to proprietary trading. Presto Research is a research unit within Presto Labs, providing crypto market intelligence drawn from the collection of Preso Lab's world-class experts in quant trading, web3, and TradFi.

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Authors

Jin H. Jung, Head of Trading Research : Twitter, LinkedIn

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