“Daily abnormal returns and price effects in the “passion investments” market”

Alex Plastun
Ahniia Havrylina
Liudmyla Sliusareva
Nataliya Strochenko
Olga Zhmaylova


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Abstract
This paper explores price effects in the “passion investments” market after days with abnormal returns. To do this, daily prices for stamps and diamonds over the periods 1999–2021 and 1989–2021 are analyzed. The following hypothesis is tested: One-day abnormal returns create stable patterns in price behavior on the next day. Statistic tests (t-test, ANOVA, Mann–Whitney U test, modified cumulative abnormal returns approach, regression analysis with dummy variables) confirm the presence of price patterns related to extreme returns: price fluctuations on the day after extreme returns are higher than returns on “normal” days. On the days after positive abnormal returns, the momentum effect is detected. Contrarian effect is typical for the days after negative abnormal returns. A trading strategy based on detected price effects showed the presence of exploitable profit opportunities. Results of this paper provide additional pieces of evidence in favor of inconsistencies between the efficient market hypothesis and practice and can be used by traders to generate extra profits in the “passion investments” market.

INTRODUCTION
Pandemic and lockdowns created the never seen before situation in the financial markets. Monetary and fiscal stimulus have injected trillions of dollars into financial markets. As a result, prices in the stock markets, commodity markets, and cryptocurrency markets have increased significantly. Prices for alternative assets have demonstrated significant growth as well. For example, diamond prices have tripled since the start of the pandemic until the fall of 2021; the stamps index has doubled. Interest in alternative assets has increased, but in the academic literature, this field is relatively unexplored (compared with traditional assets).

The efficiency of the “passion investments” market (includes five wines, works of art, antique cars, colored diamonds, stamps, and other alternative assets) is not widely discussed among academicians especially in the aspect of patterns in price behavior, market anomalies, and potential of price patterns exploitation.

This paper aims to fill one of these gaps. From time-to-time prices in the financial markets tend to demonstrate abnormal returns (caused by new information arrival or market overreactions). The issue of price overreactions is widely discussed for the case of traditional assets (FOREX, stock market, commodity market) by De Bondt and Thaler (1985), Bremer and Sweeney (1991), Choi and Jayaraman (2009),...
Caporale and Plastun (2020a, 2020b, 2021), etc. However, none of them has focused on the alternative assets and “passion investments” in particular.

Based on results provided by Caporale and Plastun (2020a, 2020b, 2021) price dynamics on the day after abnormal returns, as a rule, is typical and can be described as a momentum or contrarian effect. The momentum effect is observed in the emerging stock markets, oil prices, and most cryptocurrency markets. Contrarian effect is typical for the FOREX (Caporale & Plastun, 2020a), developed stock markets, gold prices (Caporale & Plastun, 2021) and Bitcoin (Caporale & Plastun, 2020b). Thus, the less efficient the market, the more time it needs to incorporate new information (markets underreact). And vice versa, more efficient markets absorb new information very fast but tend to overreact.

The “passion investments” market never has been an object of such research. Still, it is very interesting to see whether abnormal returns in this market generate specific patterns in price behavior and to find out whether these patterns can help to “beat the market” – generate abnormal profits from trading.

1. LITERATURE REVIEW

Existing literature provides a lot of results in favor of price patterns in financial markets caused by abnormal price changes. The first evidence was obtained by De Bondt and Thaler (1985), who showed that if prices in the US stock market overreact in a given period, in the next period they tend to demonstrate contrarian movement. Bremer and Sweeney (1991) used daily data and find the same: after significant negative daily returns (exceeding 10%) price usually increase on the next day averaged. Similar results were detected for the case of the FOREX (Caporale & Plastun, 2020a), commodity (Cutler et al., 1991), and cryptocurrency (Caporale & Plastun, 2020b) markets.

Alternative investment instruments (fine wine, art, diamonds, stamps, etc.) are characterized by several specific features compared with traditional ones. These features include high entry barriers and high investment risks, issues with the valuation of the assets, higher transactional costs including diligence costs and lower trading volumes, lack of data and information (Fischer & Firer, 1985). Still, they have higher returns and their Sharpe ratio outperforms significantly (Lucey & Devine, 2015).

As a result, alternative investments are widely discussed in academic papers. Cardebat and Jiao (2018) showed that stock markets have a long-term relationship with fine wine markets. Worthington and Higgs (2003) established short-term and long-term co-movements between art and stock markets. Analyzing diamonds, Auer (2014) concluded that they are weak safe haven assets and weak hedge against the stock market.

Bouri et al. (2018) found that wine performs better than the US and UK stocks, bonds, gold, and residential housing index. Masset and Weiskopf (2018) showed that during economic turmoil, wine performance diminished less than for conventional assets. Faye et al. (2015) concluded that yields generated in financial markets are reinvested in wine markets. Mei and Moses (2002) showed that art outperformed bonds and treasury bills; however, equity performed even better, considering volatility. Renneboog and Spaenjers (2013) found that art performs at the level of corporate bonds, but with higher risk, and there is a low correlation of art with other traditional assets. Dimson et al. (2015) determined that wine performs better than stamps and art, but not equities. Dimson and Spaenjers (2011) showed that the real return on British stamps since the 1990s is lower than that of equities but higher than that of bonds and bills, with risk comparable to the risk of equities. Similar results but for the US classical collectible stamps are found by Grable and Chen (2015).

Masset and Henderson (2010) suggested the presence of inefficiency in the wine market. Lean and Chong (2012) examined the monthly effect in fine wine markets and revealed that there is a May effect in Liv-ex Claret Chip and Liv-ex 100, March effect in Liv-ex 500, and June effect in Liv-ex Investable. As a result, abnormal returns can be generated by buying wine in the month with the
lowest average return and selling it in the month with the highest average return.

Erdős and Ormos (2013) rejected the random walk hypothesis and identified great positive autocorrelations in fine wine returns. The positive autocorrelation of returns is confirmed by David et al. (2013). Bouri et al. (2017) illustrated that shock to the market is transitory and wine series tend to return to the mean; hence, they are predictable. Fernandez-Perez et al. (2019) found weak evidence of mean-reversion and strong evidence of autoregressive effects.

Scott and Yelowitz (2010) explored price anomalies in the diamonds market and found that buyers are ready to pay premiums of 18% for a diamond that is 0.5-carat rather than for a diamond that is slightly less and between 5% and 10% for a 1.0-carat diamond rather than a 0.99-carat diamond.

Despite several pieces of evidence against the efficiency of the alternative investments’ markets, price effects after one-day abnormal returns are not explored yet. This paper aims to show that abnormal returns generate price patterns in the alternative investments market, which can be used to generate exploitable profit opportunities. Therefore, this analysis expands the existing literature and reveals new evidence regarding market anomalies in the alternative investments market.

2. DATA, METHODOLOGY AND HYPOTHESIS

To analyze price effects caused by abnormal returns in the “passion investments” market, daily data on two alternative assets are used: diamonds (WORLD-DS Diamonds & Gems – PRICE INDEX) and stamps (Stanley Gibbons Stamp Index) over the periods April 3, 1989–October 11, 2021, and October 11, 1999–October 11, 2021, respectively. The data sources are Stanley Gibbons Group (n.d.) and Fairfield County Diamonds (Diamond Search Engine, n.d.). The following hypothesis is tested in this paper:

\[ R_i = \left( \frac{\text{Close}_i}{\text{Close}_{i-1}} - 1 \right) \cdot 100\%, \]

where \( R_i \) – returns on the \( i \)-th day in %, \( \text{Close}_{i-1} \) – close price on the \((i-1)\)-th day, \( \text{Close}_i \) – close price on the \( i \)-th day.

Abnormal returns are calculated as proposed by Caporale and Plastun (2020b). Positive and negative abnormal returns are defined using equations 2 and 3 (respectively):

\[ R_i > (\overline{R}_n + \delta_n), \]

\[ R_i > (\overline{R}_n - \delta_n), \]

where \( \overline{R}_n \) is the average daily returns for the period \( n \), \( \delta_n \) is the standard deviation calculated for daily returns over the period \( n \).

Statistical tests both parametric and non-parametric test null hypothesis \((H0): \) returns on usual days and on days after abnormal returns belong to one general population. If \( H0 \) is rejected, pieces of evidence in favor of anomaly are found.

A simple regression analysis with dummy variables is implemented in the following manner:

H1: One-day abnormal returns create stable patterns in price behavior on the next day.
The result from each trade is calculated as follows:

\[
\%result = \frac{100\% \cdot P_{\text{open}}}{P_{\text{close}}},
\]

where \( P_{\text{open}} \) – trade opening price, \( P_{\text{close}} \) – trade closing price.

To provide evidence that obtained results differ from random trading, a \( t \)-test is carried out. A rejection of the null hypothesis allows one to conclude that results belong to the different general population: Means trading strategies generate results that are different from the random ones and generated profits are not a coincidence.

3. EMPirical RESULTS

The full empirical results for the positive and negative abnormal returns are provided in Appendix A. This section provides a summary of these results and their discussion.

Average analysis results are represented in Table A1. Their visual interpretation is provided in Figure 1.

As can be seen, average returns on usual days are negative and close to 0%. Which is in line with the random walk hypothesis. However, returns on days after abnormal days demonstrate a stable pattern: prices tend to increase.

The next step is to define the statistical significance of detected price differences. To do this both parametric and non-parametric tests are applied. Results are presented in Tables A2 (\( t \)-test), A3 (ANOVA analysis), and A4 (Mann–Whitney U test), and they are mixed. According to \( t \)-test and ANOVA analysis, the size of price fluctuations after the days with abnormal returns differ from those on usual days. Non-parametric tests confirm anomaly only for the case of stamps data after positive abnormal returns.

To find further evidence, regression analysis with dummy variables (Table A5) and a modified CAR approach (Table A6) are used. They confirmed the presence of price effects caused by daily abnormal returns. A dummy variable (data concern the day after abnormal return) provides a statistically significant positive impact on average return. Returns
on the days after abnormal return generate a trend in the cumulative abnormal returns that indicates in favor of pattern presence price behavior.

To see whether detected patterns can be exploited, a trading simulation approach is applied. The trading strategy for all of the analyzed cases is as follows: open long position right after the day of the abnormal returns and close it at the end of that day. Trading simulation results are presented in Table 1. Visual interpretation of trading simulation results is provided in Figure 2. As can be seen, they are rather stable with the only exception: Stamps (positive returns) – in this case, the anomaly is extremely strong as well as trading opportunities.

As can be seen in most of the cases, the number of successful trades in 3 of 4 cases is close to 50%, which is in line with the random nature of price movements. However, profits generated from trading in most of the cases differ from random trading. This evidences in favor of anomaly presence.

The summary of the results is presented in Table 2.

Table 1. Results of a trading strategy based on detected price patterns

<table>
<thead>
<tr>
<th>Case</th>
<th>Number of trades, units</th>
<th>Number of successful trades, unit</th>
<th>Number of successful trades, %</th>
<th>Profit, %</th>
<th>Profit % per year</th>
<th>Profit % per trade</th>
<th>t-test calculated value</th>
<th>t-test status</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stamps (positive returns)</td>
<td>275</td>
<td>174</td>
<td>63%</td>
<td>292%</td>
<td>14.58%</td>
<td>1.06%</td>
<td>3.50</td>
<td>rejected</td>
</tr>
<tr>
<td>Stamps (negative returns)</td>
<td>207</td>
<td>101</td>
<td>49%</td>
<td>38%</td>
<td>1.92%</td>
<td>0.19%</td>
<td>0.60</td>
<td>not rejected</td>
</tr>
<tr>
<td>Diamonds (positive returns)</td>
<td>956</td>
<td>480</td>
<td>50%</td>
<td>252%</td>
<td>8.39%</td>
<td>0.26%</td>
<td>1.72</td>
<td>rejected*</td>
</tr>
<tr>
<td>Diamonds (negative returns)</td>
<td>831</td>
<td>410</td>
<td>49%</td>
<td>280%</td>
<td>9.34%</td>
<td>0.34%</td>
<td>2.11</td>
<td>rejected</td>
</tr>
</tbody>
</table>

Note: * means significant with 90%.

Table 2. Summary of results for the stamps and diamonds: The case of negative and positive returns

<table>
<thead>
<tr>
<th>Case</th>
<th>Average analysis</th>
<th>Students t-test</th>
<th>ANOVA</th>
<th>Mann-Whitney test</th>
<th>Modified CAR</th>
<th>Regression with dummy variables</th>
<th>Trading simulation</th>
<th>Overall</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stamps (positive returns)</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>7</td>
</tr>
<tr>
<td>Stamps (negative returns)</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>4</td>
</tr>
<tr>
<td>Diamonds (positive returns)</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>-</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>6</td>
</tr>
<tr>
<td>Diamonds (negative returns)</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>-</td>
<td>-</td>
<td>+</td>
<td>+</td>
<td>5</td>
</tr>
</tbody>
</table>

Note: + indicates that the specific method applied managed to detect the anomaly and + shows that the presence of anomaly is not confirmed.
Based on the results from Table 2 it can be concluded that prices tend to demonstrate predictable behavior after days with abnormal returns. For the case of positive abnormal returns, it is typical for the prices to increase on the day after – it means the momentum effect is detected in both stamps and diamonds. Positive returns are observed after the days with negative abnormal returns – it means the contrarian effect is detected. Thus, markets can’t absorb positive returns during only one day (underreaction) and it takes another to incorporate new information in prices. For the case of negative abnormal returns, it appears that markets react too strongly to the new information (overreact) and the next day prices tend to return to the equilibrium level. In general, these results are in line with those provided by Caporale and Plastun (2020a, 2020b, 2021).

Implications of these results are as follows. Academicians obtain additional evidence against the efficient market hypothesis: prices tend to generate patterns; there are overreactions and underreactions in price behavior. For practitioners (traders, investors), it is detected that price effects can be exploited to generate abnormal profits by using simple rules (buy after abnormal returns) in trading decisions.

**CONCLUSION**

This paper aims to show that abnormal returns generate price patterns in the alternative investments market, which can be used to generate exploitable profit opportunities. The following hypothesis is tested: One-day abnormal returns create stable patterns in price behavior on the next day. To do this daily data for stamps (data period October 11, 1999–October 11, 2021) and diamonds (April 03, 1989–October 11, 2021) are analyzed.

Results show that abnormal returns (both positive and negative) create specific patterns in price behavior in the “passion investments” market. After positive abnormal returns, prices for stamps and diamonds tend to increase. This is called the momentum effect in the literature. Positive returns are observed after the days with negative abnormal returns as well. This means that the contrarian effect is present.

Based on these observations it can be concluded that prices in the “passion investments” markets can’t absorb positive information during the day it appears and it takes at least another day to incorporate it in prices. It means that markets underreact. The reaction of stamp and diamond prices for the negative events is excessive: price decline is too strong. As a result, on the next day prices tend to increase. In this case, the markets overreact. Therefore, further pieces of evidence in favor of overreaction and underreaction hypotheses are found.
The contribution of this paper can be divided into 2 parts. For academicians: additional inconsistencies between the efficient market hypothesis and practice are found; prices tend to generate patterns; there are overreactions and underreactions in price behavior. For practitioners (traders, investors): detected price effects can be used to generate profits from trading.

AUTHOR CONTRIBUTIONS

Conceptualization: Liudmyla Sliusareva.
Data curation: Liudmyla Sliusareva.
Formal analysis: Liudmyla Sliusareva, Nataliya Strochenko, Olga Zhmaylova.
Investigation: Alex Plastun.
Methodology: Alex Plastun.
Project administration: Alex Plastun.
Resources: Ahniia Havrylina.
Validation: Nataliya Strochenko, Olga Zhmaylova.
Visualization: Nataliya Strochenko.
Writing – original draft: Alex Plastun, Ahniia Havrylina, Liudmyla Sliusareva, Nataliya Strochenko, Olga Zhmaylova.
Writing – review & editing: Ahniia Havrylina, Olga Zhmaylova.

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REFERENCES

### APPENDIX A

#### Table A1. Average analysis of returns on usual days and days after abnormal returns: The case of stamps and diamonds

<table>
<thead>
<tr>
<th>Case</th>
<th>Usual day</th>
<th>Day after abnormal returns</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stamps (positive returns)</td>
<td>-0.21%</td>
<td>1.06%</td>
</tr>
<tr>
<td>Stamps (negative returns)</td>
<td>-0.21%</td>
<td>0.18%</td>
</tr>
<tr>
<td>Diamonds (positive returns)</td>
<td>-0.07%</td>
<td>0.26%</td>
</tr>
<tr>
<td>Diamonds (negative returns)</td>
<td>-0.07%</td>
<td>0.34%</td>
</tr>
</tbody>
</table>

#### Table A2. T-test

<table>
<thead>
<tr>
<th>Instrument</th>
<th>Parameter</th>
<th>Usual day</th>
<th>Day after positive abnormal returns</th>
<th>Parameter</th>
<th>Usual day</th>
<th>Day after negative abnormal returns</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stamps</td>
<td>Mean, %</td>
<td>-0.21%</td>
<td>1.06%</td>
<td>Mean, %</td>
<td>-0.21%</td>
<td>0.18%</td>
</tr>
<tr>
<td></td>
<td>Stand. Dev., %</td>
<td>2.11%</td>
<td>5.03%</td>
<td>Stand. Dev., %</td>
<td>2.11%</td>
<td>4.46%</td>
</tr>
<tr>
<td></td>
<td>Number of values</td>
<td>2057</td>
<td>275</td>
<td>Number of values</td>
<td>2057</td>
<td>207</td>
</tr>
<tr>
<td>Diamonds</td>
<td>Mean, %</td>
<td>-0.07%</td>
<td>0.26%</td>
<td>Mean, %</td>
<td>-0.07%</td>
<td>0.34%</td>
</tr>
<tr>
<td></td>
<td>Stand. Dev., %</td>
<td>1.93%</td>
<td>4.75%</td>
<td>Stand. Dev., %</td>
<td>1.93%</td>
<td>4.61%</td>
</tr>
<tr>
<td></td>
<td>Number of values</td>
<td>6509</td>
<td>956</td>
<td>Number of values</td>
<td>6509</td>
<td>831</td>
</tr>
<tr>
<td></td>
<td>t-criterion</td>
<td>4.14</td>
<td>1.27</td>
<td>t-criterion</td>
<td>4.14</td>
<td>1.27</td>
</tr>
<tr>
<td>Diamonds</td>
<td>Null hypothesis rejected</td>
<td>confirmed</td>
<td>Null hypothesis not rejected</td>
<td>Anomaly confirmed</td>
<td>not confirmed</td>
<td></td>
</tr>
</tbody>
</table>

#### Table A3. ANOVA test

<table>
<thead>
<tr>
<th>Case</th>
<th>F</th>
<th>p-value</th>
<th>F critical</th>
<th>Null hypothesis</th>
<th>Anomaly</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stamps (positive returns)</td>
<td>57.08</td>
<td>0.00</td>
<td>3.85</td>
<td>rejected</td>
<td>confirmed</td>
</tr>
<tr>
<td>Stamps (negative returns)</td>
<td>5.12</td>
<td>0.02</td>
<td>3.85</td>
<td>rejected</td>
<td>confirmed</td>
</tr>
<tr>
<td>Diamonds (positive returns)</td>
<td>15.47</td>
<td>0.00</td>
<td>3.84</td>
<td>rejected</td>
<td>confirmed</td>
</tr>
<tr>
<td>Diamonds (negative returns)</td>
<td>21.82</td>
<td>0.00</td>
<td>3.84</td>
<td>rejected</td>
<td>confirmed</td>
</tr>
</tbody>
</table>

#### Table A4. Mann–Whitney U test

<table>
<thead>
<tr>
<th>Case</th>
<th>Adjusted H</th>
<th>d.f.</th>
<th>P-value</th>
<th>Critical value</th>
<th>Null hypothesis</th>
<th>Anomaly</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stamps (positive returns)</td>
<td>38.55</td>
<td>1.00</td>
<td>0.00</td>
<td>3.84</td>
<td>rejected</td>
<td>confirmed</td>
</tr>
<tr>
<td>Stamps (negative returns)</td>
<td>1.40</td>
<td>1.00</td>
<td>0.24</td>
<td>3.84</td>
<td>not rejected</td>
<td>not confirmed</td>
</tr>
<tr>
<td>Diamonds (positive returns)</td>
<td>3.72</td>
<td>1.00</td>
<td>0.05</td>
<td>3.84</td>
<td>not rejected</td>
<td>not confirmed</td>
</tr>
<tr>
<td>Diamonds (negative returns)</td>
<td>0.31</td>
<td>1.00</td>
<td>0.58</td>
<td>3.84</td>
<td>not rejected</td>
<td>not confirmed</td>
</tr>
</tbody>
</table>

#### Table A5. Regression analysis with dummy variables*

<table>
<thead>
<tr>
<th>Case</th>
<th>Multiple R</th>
<th>F-test</th>
<th>F-test</th>
<th>a0</th>
<th>a1</th>
<th>Anomaly</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stamps (positive returns)</td>
<td>0.15</td>
<td>57.08</td>
<td>(0.00)</td>
<td>-0.0021 (0.00)</td>
<td>0.0127 (0.00)</td>
<td>confirmed</td>
</tr>
<tr>
<td>Stamps (negative returns)</td>
<td>0.05</td>
<td>5.12</td>
<td>(0.02)</td>
<td>-0.0021 (0.00)</td>
<td>0.0040 (0.02)</td>
<td>confirmed</td>
</tr>
<tr>
<td>Diamonds (positive returns)</td>
<td>0.05</td>
<td>15.47</td>
<td>(0.00)</td>
<td>-0.0007 (0.02)</td>
<td>0.0034 (0.00)</td>
<td>confirmed</td>
</tr>
<tr>
<td>Diamonds (negative returns)</td>
<td>0.05</td>
<td>21.82</td>
<td>(0.00)</td>
<td>-0.0007 (0.01)</td>
<td>0.0041 (0.00)</td>
<td>confirmed</td>
</tr>
</tbody>
</table>

*Note: *p*-values are in parentheses.

#### Table A6. Modified CAR approach*

<table>
<thead>
<tr>
<th>Case</th>
<th>Multiple R</th>
<th>F-test</th>
<th>F-test</th>
<th>a0</th>
<th>a1</th>
<th>Anomaly</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stamps (positive returns)</td>
<td>0.96</td>
<td>3370.54 (0.00)</td>
<td>0.6254 (0.00)</td>
<td>0.0095 (0.00)</td>
<td>confirmed</td>
<td></td>
</tr>
<tr>
<td>Stamps (negative returns)</td>
<td>0.59</td>
<td>106.94 (0.00)</td>
<td>-0.0701 (0.00)</td>
<td>0.0022 (0.00)</td>
<td>confirmed</td>
<td></td>
</tr>
<tr>
<td>Diamonds (positive returns)</td>
<td>0.97</td>
<td>14305.02 (0.00)</td>
<td>-0.2509 (0.00)</td>
<td>0.0039 (0.00)</td>
<td>confirmed</td>
<td></td>
</tr>
<tr>
<td>Diamonds (negative returns)</td>
<td>0.01</td>
<td>21.82 (0.00)</td>
<td>3.72 (0.00)</td>
<td>0.0000 (0.80)</td>
<td>not confirmed</td>
<td></td>
</tr>
</tbody>
</table>

*Note: *p*-values are in parentheses.