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Momentum in Imperial Russia[☆]

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ABSTRACT

Some of the leading theories of momentum have different empirical predictions that depend on market composition and structure. The institutional theory predicts lower momentum profits in markets with less agency. Behavioral theories predict lower profits in markets with more sophisticated investors. In this paper, we use a dataset from a major 19th century equity market to test these predictions. We find no evidence to support the institutional theory due to the lack of delegated management. We exploit a regulatory change in the middle of our sample period to test behavioral theories. We find evidence consistent with overreaction theories of momentum.

1. Introduction

Momentum strategies, also known as relative strength strategies, are a class of long-short trading strategies that buy past winners and sell past losers. Jegadeesh and Titman (1993) first document the profitability of momentum strategies in a sample of U.S. stocks over the period 1965 to 1989. Many other studies extend this initial finding by showing momentum profitability in the post-1989 period in equity markets inside and outside of the U.S. and in other asset classes.[1] While there is an abundance of empirical evidence for momentum, the debate on its underlying mechanism remains unsettled.

Explanations for momentum divide into risk-based and behavioral theories. Risk-based theories explore cross-sectional and time-series compensation for risk. Berk et al. (1999), Johnson (2002), and Sagi and Seasholes (2007) offer theories that show how changing firm-level systematic risk and cash flow growth rates can generate momentum.[2] Daniel and Moskowitz (2016) show that extreme losses to momentum strategies in the U.S. cluster in the Great Depression and the Great Recession. This points to a potential link between the high Sharpe ratio of momentum strate-

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1 See, e.g., Rouwenhorst (1998), Jegadeesh and Titman (2001), and Asness et al. (2013).

2 Other papers proposing dynamic risk exposure include Grundy and Martin (2001), Pastor and Stambaugh (2003), Bansal et al. (2005), Liu and Zhang (2006), and Sadka (2006).

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gies and exposure to (possibly infrequent) macroeconomic shocks.

Most behavioral theories focus on psychological heuristics and biases that can lead to over- or underreaction to news about firm fundamentals. For instance, Daniel et al. (1998) propose a model in which investor overconfidence about the precision of private information generates continuing overreaction to public information, which manifests as the momentum effect. In contrast, in Hong and Stein's (1999) model, the interaction of boundedly rational agents and information frictions generate initial underreaction and subsequent overreaction. In recent work, Lou (2012) and Vayanos and Woolley's (2013) propose explanations of momentum driven by flows into and between institutional money managers conditional upon performance.[3]

Although these theories all generate the momentum effect, they have different predictions about momentum profitability conditional on market composition and structure. Tests of theoretical predictions about the source of momentum profits require significant variation for identification. In this paper, we use a comprehensive dataset of monthly stock returns from the St. Petersburg Stock Exchange in the 19th and early 20th centuries to test these predictions. The St. Petersburg Stock Exchange provides a useful setting because it has certain features that allow us to distinguish among several momentum theories.

First, it is an independent historical market record from an economy that experienced significant intertemporal macroeconomic shocks and market crashes.[4] This allows us to test some of the risk-based theories of momentum. Second, there was significant institutional variation in the types of participating traders potentially subject to behavioral biases. In particular, a regulatory change in 1893 substantially reduced the costs of speculative trading for less sophisticated investors. Third, one of the conditions proposed as an explanation for momentum—cashflows to investment funds—was absent in the sample. There was no evidence of a delegated management structure in the Russian Empire over this period.[5]

These conditions of pre-1914 Russia allow us to differentiate among some of the leading theories about momentum profits. Our results are inconsistent with the institutional theory, as the institutions that the theory relies on to generate momentum were absent, and yet we still find significant momentum profits. We also find no support for macroeconomic drivers of momentum or for a rare disaster explanation. Momentum profits are unrelated to GDP or market conditions. Moreover, they do not exhibit the crash-prone pattern observed in the U.S. market post-1926.

The major institutional change that we identified occurred in the Russian market in 1893. Liquidity increased, supporting the view that market participation by less sophisticated investors increased. Momentum profits were small before the change but large afterward. Moreover, these profits reverse over one- to five-year horizons, consistent with overreaction theories of momentum.

Our paper is part of a recent literature on documenting momentum in historical equity markets. Chabot et al. (2009) document momentum in the U.K. market over the period 1866 to 1907. Geczy and Samonov (2016) use a database of U.S. stock returns over the period 1801 to 2012. They find that momentum is consistently profitable over these two centuries. Our analysis supports these authors' findings that momentum is ubiquitous in pre-World War I markets. The focus of our paper, however, is on using the unique setting of the St. Petersburg Stock Exchange to differentiate between existing prominent explanations of momentum. Our paper also complements another study of long-term momentum returns (specifically, time-series momentum returns), namely Hurst et al. (2017).

The remainder of the paper is organized as follows. Section 2 provides the historical background. Section 3 presents the data and methodology. Section 4 establishes the results. Section 5 concludes the paper.

2. Historical background

From 1732 to 1918, St. Petersburg was the capital of the Russian Empire. The St. Petersburg Exchange was established in the early 1800s, approximately 100 years after the founding of the city of St. Petersburg. According to Lizunov (2004), the first stocks traded on the St. Petersburg Stock Exchange in the early 1830s. As the Russian economy developed, the number of corporations with shares traded on the St. Petersburg Stock Exchange grew rapidly. By 1914, more than 200 Russian corporations had their shares listed.[6] The St. Petersburg Stock Exchange closed down due to World War I in July 1914. It reopened for two months in 1917 before it closed down again for 74 years after the Russian Revolution of 1917. Market participants consisted mainly of ruling elites, company insiders, and wealthy merchants. Compared to a modern stock market, delegated managers such as mutual funds were notably absent.[7]

During most of our sample period of January 1865 to July 1914, the Russian stock market was regulated by the corporate law of 1836. The goal of the law was to encourage corporate capitalism in the style of Western Europe while maintaining bureaucratic control in the

[3] Proposed behavioral heuristics that can generate momentum also include conservatism (Barberis et al., 1998), the disposition effect (Grinblatt and Han, 2005; Shumway and Wu, 2005), culture (Chui et al., 2010), and cognitive dissonance (Antoniou et al., 2013).

[4] The majority of academic studies of the momentum effect use the database of U.S. stocks maintained by the Center for Research in Security Prices (CRSP). The CRSP dataset starts in 1926. Even with the many papers that use different samples, the issue of whether these samples are truly independent remains. While studies such as Rouwenhorst (1998) expand the sample internationally, others also document cross-country correlations (Griffin et al., 2003, cf.). In particular, Asness et al. (2013) find a strong common factor structure among momentum returns from a set of diverse markets and asset classes.

[5] The fund industry existed in the U.K. during this period but invested almost exclusively in bonds.

[6] See Owen (1991).

[7] According to Abramov and Akshentceva (2014), the first mutual funds did not appear in Russia until 1997. Over part of the period of our study, investment funds in London traded in Russian securities, which raised the possibility of institutional influence via international channels. Virtually all British funds, however, held fixed-income securities. See, e.g., Goetzmann and Ukhov (2006) for details.

traditional Russian style. It guarded against stock market speculation primarily through the strict ban on futures agreement. According to Timofeev (1903), the law categorically stated that:

> Any agreement among private persons, whether on the exchange or outside it, regarding the purchase and sale of stocks or notes not for cash, and with delivery at a future date and at a certain price, is absolutely forbidden. Furthermore, if such agreements are made known in court, they shall be considered null and void, and those individuals convicted of having made such agreements shall be punished under the law against games of chance. Brokers or notaries who dare to conclude such agreements shall be dismissed from their posts. (p. 141)

In the decades that followed, shortcomings of the law of 1836 became apparent and caused the tsarist policy markers to consider numerous reforms. However, due to the bureaucrats' more basic impulses of inertia and fear of change, most of these plans failed. One notable exception was the Russian law *PSZ* 3–9741, enacted on June 8, 1893. It removed the aforementioned restrictions that prohibited futures dealings in stocks.[8] As a result of this new law, a speculative fever swept across Imperial Russia in the fall of 1893. As reported in Owen (1991), "instead of being confined [...] to the Hotel Demuth in Petersburg and, in Moscow, the Chizhov Court and the apartment of a Georgian princess, [trading activities] enveloped all the big hotels, as crowds of people who owned interest-bearing securities sold them to buy dividend-paying stocks whose values were soaring." (p. 138)

In the following sections, we examine this unique setting in detail using hand-collected share price and dividend data to test hypotheses about the specific mechanism driving the momentum effect. The results shed light on how unfettered speculation by a broad spectrum of the public can rapidly and radically affect market efficiency.

3. Data and methodology

Our dataset of end-of-month stock prices for all companies listed on the St. Petersburg Stock Exchange over the period January 1865 to July 1914 was hand-collected from five different sources.[9] From the periods of January 1865 to December 1890, January 1893 to December 1893, and January 1897 to December 1904, end-of-month prices are from the Yearbook of the Finance Ministry. From January 1891 to November 1892, end-of-month prices are from the Bulletin of the Finance, Industries, and Trade. For the month of December 1892, end-of-month stock prices are from the Stock Exchange Newsletter. For the periods of January 1894 to December 1896, January 1905 to December 1911, and January 1914 to July 1914, end-of-month stock prices are from the Commercial and Industrial Newspaper. Finally, from January 1912 to December 1913, end-of-month stock prices are directly from the St. Petersburg Stock Exchange. The data are available for download on the website of the International Center for Finance at the Yale School of Management.

The methodology that we used to process the raw data closely follows Goetzmann et al. (2001). The month-end prices were obtained by searching the end-of-month issues for the last transaction price for each stock that month. When no transaction took place in the last week, the latest bid and ask prices were averaged. In total, we collected 43,736 end-of-month stock prices for 598 companies. From these, we calculated 38,090 monthly returns for 543 firms. There were three instances of 50% price drops, and we assume that they represent stock splits.[10] We computed only the returns when two adjacent prices were available, in a manner similar to that of CRSP. The number of firms in the universe averaged 64. It reached a high point in April 1912, with 206 listed firms.[11] The fact that the number of firms concurrently listed peaked at under 210, while the total number of firms in the database exceeded 540 indicates that, not only did firms appear during the sample period, but that they also disappeared. We do not have data on firm failures nor delisting returns. To ensure the robustness of our main results, we reproduce them in the online Internet Appendix under the assumption that exit firms all have −100% returns.

We obtained dividend data for the period 1885 to 1915 from the same sources. In total, we have 4,951 annual dividend payment observations for 478 companies. Because we do not know whether these publications always reported dividends for all stocks listed on the St. Petersburg Stock Exchange, we do not know whether exclusions of dividends meant that they were not paid, or whether we failed to find them. We include robustness checks in the Internet Appendix to address potential issues caused by incomplete dividend coverage. The number of stocks for which we have an unbroken series of annual dividend payment observations is small. In analysis that follows, we assume that the dividends were paid at year-end, but changing this assumption does not change our results.

We control for market risk exposure in our asset pricing tests. Because we lack data on shares outstanding, we use a simple procedure to construct a price-weighted market index. For each month in our sample, we calculate monthly returns for all stocks that trade in two consecutive months. We weight these returns by the price at the beginning of the two months. The return of the price-weighted index over period t, $r_{M,\,t}$, is defined as

$$r_{M,t} \equiv \sum_{i=1}^{N_t}(r_{i,t}w_{i,t}) = \sum_{i=1}^{N_t}\left(\frac{P_{i,t}+D_{i,t}}{P_{i,t-1}}\frac{P_{i,t-1}}{\sum_{j=1}^{N_t}P_{j,t-1}}\right)$$
$$= \frac{\sum_{i=1}^{N_t}(P_{i,t}+D_{i,t})}{\sum_{j=1}^{N_t}P_{j,t-1}}. \tag{1}$$

[8] According to Owen (1991), "*PSZ* 3–9741 implicitly legalized time deals on stocks and bonds by forbidding such deals on gold currency and securities reckoned in gold, solely for the purpose of realizing a speculative profit." (p. 139)

[9] This is the same dataset used by Borodkin and Perelman (2011).

[10] Assuming otherwise does not change our results.

[11] In the old NYSE dataset of Goetzmann et al. (2001), the number of firms peaked at 114 in May 1883.

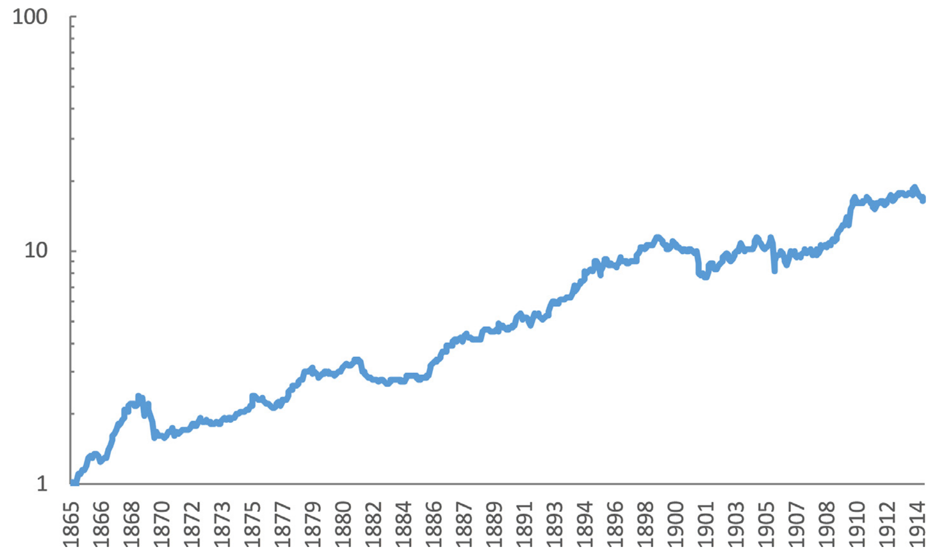

Fig. 1. Price-weighted SPSE index. This figure shows the cumulative return of the price-weighted SPSE index. The sample period is January 1865 to July 1914.

Table 1
Summary statistics.
This table presents summary statistics for the monthly return of the price-weighted SPSE index. The means and standard deviations are in percentages and annualized. The sample period is January 1865 to July 1914.

Date	Arithmetic mean	Geometric mean	Standard deviation
2/1865–7/1914	6.41	5.78	11.03
2/1865–12/1869	11.24	9.70	17.06
1/1870–12/1879	7.07	6.76	7.59
1/1880–12/1889	5.02	4.77	6.98
1/1890–12/1899	8.80	8.32	9.47
1/1900–12/1909	2.85	1.85	14.26
1/1910–7/1914	5.70	4.98	11.71

Here, $r_{i,\,t}$ represents the return of security i over the period t, and $w_{i,\,t}$ represents the weight of security i over period t, which is equal to $P_{i,t-1}/\sum_{j=1}^{N_t} P_{j,t-1}$, as the index is price-weighted. Using a price-weighted index offers the benefit that its return closely approximates return to a buy-and-hold portfolio over the period and, as such, is not sensitive to bid-ask bounce bias (Canina et al., 1998).

In addition to stock price data, we also obtained macroeconomic data from Vinogradov (2016). These include dates of financial crises, which we take to encompass banking crises, market crises, and currency crises. Vinogradov also provides data on real GDP at the annual frequency. We use these data to specifically identify states of the world when investors have high marginal utility.

4. Results

Fig. 1 shows the cumulative return of the price-weighted St. Petersburg Stock Exchange (SPSE) index on a log scale. Table 1 shows summary statistics for the underlying monthly return of the index for the period February 1865 to July 1914 as well as for each decade of the period.

Over the entire period, the annual geometric return of the SPSE index is 5.78%, but there are periods of higher and lower growth. The annual geometric return is 9.7% in the second half of the 1860s and 1.85% in the 1900s. The long-term mean is slightly below the 5.82% annual growth experienced by the NYSE index over the same period.[12] This long-term mean, however, is not a good estimate of the equity premium provided by the St. Petersburg stock market because we know that, ex post, buy-and-hold investors lost 100% of their investments after the Russian Revolution of 1917. Finally, we observe that the volatility of the index varies considerably. It is 11.03% over the entire sample period, with a high of 17.06% in the 1860s and a low of 6.98% in the 1880s. This is below the 14.52% volatility experienced by the NYSE index over the same period.

4.1. Momentum profits

We investigate the profitability of momentum strategies in this no-delegated-management setting. Vayanos and Woolley's (2013) institutional theory is based on flows between institutional money managers. Flows are triggered by changes in fund managers' efficiency, which investors can infer from past performance. Momentum arises if flows exhibit inertia and because rational prices underreact to expected future flows. According to this theory, because a delegated management structure is notably absent in our setting, the momentum effect should be relatively weak.[13] Stated differently, we ask whether the existence of a delegated management structure is a necessary condition for price continuation patterns.

[12] In our calculations we use the NYSE index constructed by Goetzmann et al. (2001) over the same sample period.

[13] This prediction is not unique to the institutional theory. The data snooping critique of the momentum effect also predicts that there will be no momentum in this out-of-sample setting.

Table 2
Returns of momentum portfolios.
The momentum portfolios are formed based on *J*-month lagged returns and held for *K* months. The stocks are ranked in ascending order on the basis of the lagged returns. An equally weighted portfolio of stocks in the lowest past return tercile is the sell portfolio, and an equally weighted portfolio of the stocks in the highest return tercile is the buy portfolio. This table presents the average monthly returns of these portfolios. The values of *J* and *K* for the different strategies are indicated in the first column and row, respectively. The momentum portfolios in Panel A are formed using returns over the entire portfolio formation period, while those in Panel B have the most recent month in the formation period skipped. *t*-statistics are in parentheses. The sample period is January 1865 to July 1914.

		Panel A				Panel B			
	J	*K*= 3	6	9	12	*K*= 3	6	9	12
3	Buy	0.0060	0.0070	0.0071	0.0074	0.0064	0.0072	0.0073	0.0073
		(3.99)	(4.89)	(5.21)	(5.40)	(4.30)	(4.99)	(5.30)	(5.33)
	Sell	0.0045	0.0041	0.0041	0.0033	0.0037	0.0040	0.0042	0.0038
		(3.13)	(3.05)	(3.02)	(2.51)	(2.56)	(2.88)	(3.08)	(2.89)
	Buy minus sell	0.0014	0.0029	0.0029	0.0041	0.0023	0.0031	0.0031	0.0036
		(1.18)	(2.93)	(3.40)	(5.31)	(2.08)	(3.32)	(4.03)	(5.15)
6	Buy	0.0067	0.0074	0.0080	0.0079	0.0075	0.0075	0.0081	0.0079
		(4.44)	(5.12)	(5.67)	(5.59)	(4.90)	(5.22)	(5.68)	(5.50)
	Sell	0.0036	0.0036	0.0028	0.0027	0.0030	0.0034	0.0027	0.0029
		(2.60)	(2.56)	(2.06)	(2.03)	(2.17)	(2.37)	(1.97)	(2.15)
	Buy minus sell	0.0031	0.0038	0.0052	0.0053	0.0040	0.0039	0.0051	0.0048
		(2.44)	(3.29)	(5.04)	(5.66)	(3.29)	(3.54)	(5.29)	(5.53)
9	Buy	0.0072	0.0082	0.0082	0.0079	0.0076	0.0081	0.0081	0.0077
		(4.83)	(5.67)	(5.69)	(5.48)	(5.00)	(5.54)	(5.53)	(5.26)
	Sell	0.0034	0.0025	0.0025	0.0027	0.0028	0.0023	0.0025	0.0030
		(2.32)	(1.72)	(1.80)	(2.00)	(1.96)	(1.65)	(1.81)	(2.28)
	Buy minus sell	0.0037	0.0057	0.0057	0.0053	0.0045	0.0060	0.0056	0.0048
		(2.83)	(4.80)	(5.04)	(4.94)	(3.62)	(5.11)	(5.13)	(4.63)
12	Buy	0.0085	0.0085	0.0082	0.0079	0.0087	0.0083	0.0080	0.0075
		(5.71)	(5.81)	(5.66)	(5.45)	(5.66)	(5.52)	(5.40)	(5.09)
	Sell	0.0021	0.0023	0.0025	0.0030	0.0014	0.0021	0.0025	0.0032
		(1.47)	(1.64)	(1.86)	(2.19)	(0.99)	(1.49)	(1.79)	(2.36)
	Buy minus sell	0.0065	0.0064	0.0058	0.0052	0.0074	0.0063	0.0057	0.0046
		(5.11)	(5.17)	(4.88)	(4.55)	(5.83)	(5.03)	(4.79)	(4.08)

We follow Jegadeesh and Titman (1993) in forming the momentum strategies. The portfolios are formed based on *J*-month lagged returns and held for *K* months. The stocks are ranked in ascending order on the basis of the lagged returns. An equally weighted portfolio of stocks in the lowest past return tercile is the sell portfolio, and an equally weighted portfolio of the stocks in the highest return tercile is the buy portfolio. Table 2 presents the average monthly returns of these portfolios for values of *J* and *K* that vary from a quarter to a year. To ensure that our results are robust to the effect of nonsynchronous trading and the bid-ask bounce, which can be more important in our setting than in modern markets, we also produce results for which we skip the most recent month in the portfolio formation period.

Interestingly, in our Russian sample, momentum strategies are consistently profitable across different values of *J* and *K*, with the exception of the case in which (J, K) = (3, 3). Similar to the results originally provided by Jegadeesh and Titman (1993), the most successful zero-cost strategy selects stocks based on their returns over the previous 12 months and then holds the portfolio for 3 months. As shown in Panel A, this strategy yields 65 basis points per month when there is not a lag between the portfolio formation period and the holding period. Panel B shows that the same strategy yields 74 basis points per month when there is a one-month lag between the formation period and the holding period.[14] In general, the returns are higher when there is a lag between the formation period and the holding period (Panel B) than when the formation period and the holding period are contiguous (Panel A).

A natural question to ask next is whether exposures to the market factor can explain the observed momentum profits.[15] We use the price-weighted SPSE index to proxy for the market portfolio. Table 3 shows results from adjusting for market risk in two ways: 1) using the simple market model, and 2) using the market model in which betas are allowed to vary with market conditions[16].

Similar to the results presented in Table 2, the risk-adjusted excess returns are both economically meaningful and statistically significant. The raw profits are generally higher than the excess returns adjusted by the simple market model, which, in turn, are generally higher than the

[14] The momentum strategy in which (J, K) = (12, 1) and in which the most recent month in the portfolio formation period is skipped delivers monthly profits of 80 basis points (t = 5.87) and monthly alphas of 55 basis points (t = 3).

[15] We do not have the data to construct the small-minus-big (SMB) and high-minus-low (HML) factors of Fama and French's (1993) three factor model.

[16] Rouwenhorst (1998) is one of the first papers to point out momentum strategies' time-varying factor exposures and to use such an adjustment methodology. See also Grundy and Martin (2001).

Table 3
Risk-adjusted excess returns.
The momentum portfolios are formed based on J-month lagged returns and held for K months. The stocks are ranked in ascending order on the basis of the lagged returns. An equally weighted portfolio of stocks in the lowest past return tercile is the sell portfolio, and an equally weighted portfolio of the stocks in the highest return tercile is the buy portfolio. This table presents the risk-adjusted returns of the zero-cost, buy minus sell, portfolios. The values of J and K for the different strategies are indicated in the first column and row, respectively. The returns in Panel A are adjusted by regressing on the excess return of the price-weighted SPSE index. The returns in Panel B are adjusted by running regressions of the form $r_t = \alpha + \beta^{+} U_t r_{M,t} + \beta^{-}(1 - U_t) r_{M,t} + \epsilon_t$, where U_t is a dummy variable that is one if the excess return of the SPSE index is nonnegative, and zero otherwise. t-statistics are in parentheses. The sample period is January 1865 to July 1914.

J	K=	3	6	9	12
Panel A: Risk-adjusted excess returns					
3		0.0023	0.0031	0.0031	0.0036
		(2.08)	(3.32)	(4.03)	(5.16)
6		0.0040	0.0039	0.0051	0.0048
		(3.33)	(3.55)	(5.32)	(5.59)
9		0.0045	0.0060	0.0056	0.0047
		(3.63)	(5.12)	(5.14)	(4.65)
12		0.0074	0.0063	0.0057	0.0046
		(5.92)	(5.07)	(4.83)	(4.14)
Panel B: Market dependent risk-adjusted excess returns					
3		0.0021	0.0030	0.0026	0.0032
		(1.39)	(2.39)	(2.47)	(3.40)
6		0.0036	0.0040	0.0045	0.0047
		(2.21)	(2.69)	(3.48)	(4.01)
9		0.0048	0.0053	0.0050	0.0048
		(2.84)	(3.38)	(3.38)	(3.48)
12		0.0061	0.0049	0.0047	0.0042
		(3.60)	(2.93)	(2.96)	(2.80)

excess returns adjusted by the market model in which betas are allowed to vary. Overall, excess returns of the momentum strategies cannot be accounted for by market risk adjustments.

Following the momentum literature, we focus the rest of the paper on the momentum strategy in which (J, K) = (6, 6) and the most recent month in the portfolio formation period is skipped. The results for this strategy are representative of the results for the other strategies and are available upon request. Fig. 2 provides a plot of the cumulative returns of the buy portfolio and the sell portfolio of this strategy.

4.2. The risk of momentum

Most rational theories of momentum posit its realized profits as compensation for risk. This includes time-varying systematic risk and crash risk. The model of Berk et al. (1999), one of the first in this line of research, is based on firms making optimal investment choices and having their risks change through time. Firms with positive momentum tend to be those that have encountered profitable investment opportunities. As they take advantage of those opportunities, their systematic risks increase. The simulations in the paper qualitatively reproduce momentum profitability at various horizons, but those horizons are considerably longer than the ones empirical researchers have found in the data.

Perhaps the most direct way of examining the influence of risk is to analyze momentum profits during good and bad economic states. If momentum is risky, then it should underperform in states of the world when investors have high marginal utility. Studies using modern data show conflicting results. On the one hand, Chordia and Shivakumar (2002) use data from the U.S. to provide evidence in support of the risk-based view. On the other hand, using a large international dataset covering 40 countries, Griffin et al. (2003) find significant momentum profits across both good and bad economic states. Following these papers, we use variables such as GDP growth and market return to

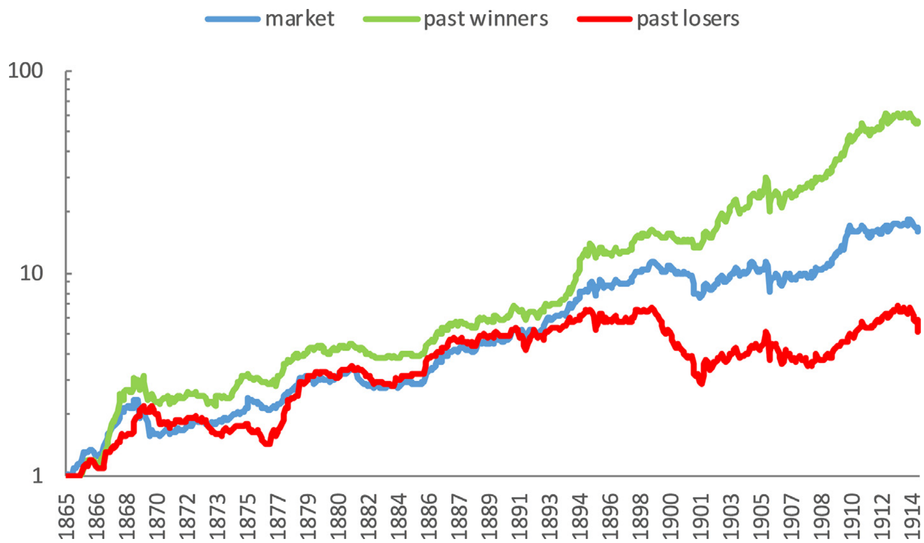

Fig. 2. Performance of past winners and losers. The momentum portfolios are formed based on six-month lagged returns and held for six months. The stocks are ranked in ascending order on the basis of the lagged returns. An equally weighted portfolio of stocks in the lowest past return tercile is the sell portfolio, and an equally weighted portfolio of the stocks in the highest return tercile is the buy portfolio. This figure shows the cumulative returns of the buy portfolio, the sell portfolio, as well as the price-weighted SPSE index. The sample period is January 1865 to July 1914.

Table 4
Momentum and economic states.
The momentum portfolios are formed based on six-month lagged returns and held for six months. The stocks are ranked in ascending order on the basis of the lagged returns. An equally weighted portfolio of stocks in the lowest past return tercile is the sell portfolio, and an equally weighted portfolio of the stocks in the highest return tercile is the buy portfolio. This table presents the average returns of the zero-cost, buy minus sell, portfolio in different economic states, classified annually based on whether there is a financial crisis, a GDP contraction, or a market downturn. *t*-statistics are in parentheses. The sample period is January 1865 to July 1914.

State variable (S)	$S = 0$	$S = 1$	Difference
Financial crisis	0.0036	0.0067	0.0031
	(3.04)	(2.18)	(0.95)
GDP contraction	0.0031	0.0070	0.0039
	(2.37)	(3.59)	(1.67)
Market downturn	0.0033	0.0066	0.0033
	(2.77)	(2.24)	(1.05)

Table 5
Higher-order statistics of momentum returns.
The momentum portfolios are formed based on J-month lagged returns and held for K months. The stocks are ranked in ascending order on the basis of the lagged returns. An equally weighted portfolio of stocks in the lowest past return tercile is the sell portfolio, and an equally weighted portfolio of the stocks in the highest return tercile is the buy portfolio. This table presents higher-order statistics of the zero-cost, buy minus sell, portfolios. The values of J and K for the different strategies are indicated in the first column and row, respectively. Panel A and Panel B present skewness and excess kurtosis, respectively. Panel C presents the smallest observed monthly returns. Panel D presents the largest observed monthly returns. The sample period is January 1865 to July 1914.

J	K= 3	6	9	12
Panel A: Skewness				
3	−0.10	−0.35	−0.35	−0.18
6	−0.30	−0.75	−0.20	−0.23
9	−0.62	−0.51	−0.44	−0.42
12	−0.29	−0.65	−0.58	−0.52
Panel B: Kurtosis				
3	4.98	5.33	5.24	4.49
6	3.76	6.35	4.26	4.49
9	2.82	2.72	3.51	3.44
12	2.67	4.14	4.81	5.39
Panel C: Minimum				
3	−0.12	−0.10	−0.09	−0.08
6	−0.14	−0.16	−0.11	−0.10
9	−0.12	−0.12	−0.11	−0.11
12	−0.12	−0.16	−0.16	−0.16
Panel D: Maximum				
3	0.14	0.10	0.09	0.08
6	0.13	0.13	0.11	0.11
9	0.12	0.10	0.14	0.11
12	0.15	0.14	0.16	0.15

classify good and bad states of the world for the marginal investor. Table 4 presents the average monthly returns of the momentum strategy in different economic states depending on whether there is a financial crisis, a GDP contraction, or a market downturn.

Similar to Griffin et al. (2003), we do not find significantly different average momentum returns across good and bad states of the world. Average monthly momentum profits are 67 basis points, 70 basis points, and 66 basis points in periods of financial crisis, GDP contraction, and market downturn. In contrast, they are 36 basis points, 31 basis points, and 33 basis points in good economic states. While the average profits seem to be counterintuitively higher in bad states, the differences in means are not statistically significant. Nevertheless, our results do not support the view that high average momentum profits serve to compensate investors for underperformance in bad times.

We can also examine whether momentum is prone to crashing in the St. Petersburg Stock Exchange setting, consistent with its profits being compensation for crash risk. Daniel and Moskowitz (2016) document that, in the U.S. equity market over the period January 1927 to March 2013, the momentum trade on many occasions experiences large crashes. These crashes are driven by the infrequent yet large-scale reversals of past losers. Specifically, Table 2 of their paper shows that the 15 worst monthly momentum returns range from −24.04% in January 1974 to −74.36% in August 1932. This raises the possibility that peso problems could explain momentum, i.e., high average momentum profits are compensation for bearing momentum crash risk (Rietz, 1988; Burnside et al., 2010). We investigate such peso events in our sample. For a deeper understanding of momentum and its risk, it is also important to know more about the frequency as well as the magnitude of the crashes.

Table 5 shows higher-order statistics of the momentum strategies. Panels A and B present skewness and excess kurtosis, respectively. They indicate that the momentum returns are, in general, negatively skewed and leptokurtic. The skewness coefficients average −0.4 and are an order of magnitude smaller than the skewness coefficient of −4.7, reported by Daniel and Moskowitz (2016) for momentum in the U.S. stock market. The values of excess kurtosis range from 2.67 to 6.35.

We target extreme outcomes of the return distributions. Panel C shows the minimum, or most negative, momentum return observations, and Panel D shows the maximum return observations. These panels indicate that the minimum returns are similar in magnitude to the maximum returns. More important, there is no evidence of momentum crashes similar to those documented by Daniel and Moskowitz (2016) for the modern U.S. stock market. The minimum ranges from −8% to −16%, while the maximum ranges from 8% to 16%. These results stand in stark contrast to those of Daniel and Moskowitz (2016) and suggest that crashes may not be an inherent feature of the momentum trade. We leave it for future researchers to investigate whether momentum crashes are caused by modern institutional features, such as delegated management.

4.3. The effects of a regulatory change

As noted, the government of Imperial Russia enacted the law *PSZ* 3–9741 on June 8, 1893, which removed all restrictions that prohibited futures dealings in stocks. We presume that those restrictions were more binding for small and less sophisticated investors. As a result, after the enactment of the law, market participation by those who were more likely to exhibit behavioral biases increased.

Most behavioral theories demonstrate that momentum can arise when the marginal investor relies on behavioral heuristics such as conservatism, representativeness, overconfidence, and biased self-attribution. At the same time, there is modern experimental evidence that these tendencies are all more likely in less sophisticated investors. To the extent that these behavioral tendencies cause momentum profits, we would expect the profits to be higher in the post-1893 period, when market participation by less sophisticated investors was higher.

To confirm the argument that market participation by less sophisticated investors increased after the enactment of *PSZ* 3–9741, we begin our analysis by looking at changes in aggregate liquidity. The intuition here is that less sophisticated investors tend to engage in noise trading. In Glosten and Milgrom's (1985) model, a risk-neutral market maker sets a bid-ask spread that allows expected noise-trading profits to offset expected informed-trading losses. When they believe that they face a pool with more noise traders, they react by decreasing the bid-ask spread.[17] Consistent with this prediction, both Lee et al. (1993) and Greene and Smart (1999) find a positive link between noise trading and liquidity. Because we lack detailed transaction data, we use a liquidity measure that relies on the incidence of observed zero monthly returns.[18]

Specifically, we measure illiquidity using the price-weighted proportion of zero monthly stock returns. Table 6 presents the results from our analysis on the liquidity effects of *PSZ* 3–9741. It shows averages for the full sample and the periods before and after June 1893 as well as differences in means between the two subsamples.

Over the full sample, the average incidence of zero returns is 12% for all stocks.[19] We also divide each cross-section using stock price, which we use throughout this paper as a proxy for size, to investigate cross-sectional heterogeneity. Consistent with the idea that liquidity increases with size, the average incidence of zero returns is 14.51% for low-price stocks and 11.31% for high-price stocks. More important, we see from the fourth row that liquidity improved substantially and significantly after the enactment of *PSZ* 3–9741, and that the improvement is larger among small stocks, which small investors tend to favor. The last row shows that this liquidity effect is not simply due to a trend in the underlying data. The evidence thus supports the argument that average investor sophistication decreased after *PSZ* 3–9741.

Table 6
The effects of *PSZ* 3–9741 on illiquidity.
In the spirit of Bekaert et al. (2007), the illiquidity measure is the price-weighted proportion of zero monthly stock returns. This table presents tests of the differences in illiquidity before and after *PSZ* 3–9741, a Russian law dated June 8, 1893. The law removed all restrictions that prohibited futures dealings in stocks. These dealings are defined as any purchase of stock in the absence of cash and with delivery at a certain time in the future. The results in the last row are obtained by regressing on a dummy variable that is one if the month is on or after June 1893, and zero otherwise, and a trend variable. *t*-statistics are in parentheses. The sample period is January 1865 to July 1914.

	All stocks	Low price	High price
Full sample	0.1200	0.1451	0.1131
	(21.30)	(21.85)	(19.81)
Pre-1893: 2/1865-5/1893	0.1494	0.1871	0.1390
	(18.54)	(19.32)	(16.98)
Post-1893: 6/1893-7/19147	0.0819	0.0908	0.0796
	(11.77)	(12.27)	(11.07)
Post-1893 minus pre-1893	−0.0675	−0.0963	−0.0593
	(−6.12)	(−7.53)	(−5.27)
Post-1893 minus pre-1893 controlling for trend	−0.1369	−0.2070	−0.1183
	(−6.44)	(−8.48)	(−5.42)

Next, we compare momentum profits before and after *PSZ* 3–9741 to test the prediction that they are higher in the post-1893 period due to higher participation by less sophisticated investors. Panel A of Table 7 shows our first set of results. In the first row, we see that the winners minus losers momentum strategy generates small and statistically insignificant profits of five basis points per month over the period February 1865 to May 1893. In contrast, the same momentum strategy delivers large and highly significant profits of 83 basis points per month over the period June 1893 to July 1914. The difference in average momentum profits between the pre-1893 period and the post-1893 period is 78 basis points per month and is significant at the 1% level. It is also interesting to note that the difference is contributed by both higher returns from the winners portfolio (89 basis points vs. 65 basis points) and lower returns from the loser portfolio (6 basis points vs. 56 basis points) in the later period. Similar to the liquidity effect, a trend in the momentum return cannot explain this finding.

We formally test for a structural break with unknown break date in the average return of the momentum portfolio by applying the Quandt (1960) and Andrews (1993) methodology. The null hypothesis of the Quandt-Andrews test is constancy of the mean against the alternative of a significant break of unknown timing. The methodology involves calculating a Chow (1960) *F*-statistic for all possible break dates in the interior π_0% to $(1-\pi_0)$% of the sample.[20] The *supF*-statistic is the maximum of these *F*-statistics, which does not follow the *F*-distribution. We use the critical values provided by Andrews (1993, 2003).

Fig. 3 plots these Chow (1960) *F*-statistics. The maximum *F*-statistic is obtained on August 1893, just two months after the passage of *PSZ* 3–9741. Its value, the *supF*-statistic, is 11.84 with a *p*-value of 0.01. The evidence, therefore, is consistent with the view that a structural

[17] Glosten and Milgrom (1985) assume a setting with asymmetric information. If, in contrast, there is no asymmetric information, as in Demsetz (1968), a larger pool of traders is sufficient to cause the bid-ask spread to decrease. Models of the momentum effect typically require asymmetric information.

[18] See Lesmond et al. (1999) for the theoretical treatment and Bekaert et al. (2007) for an application in emerging markets.

[19] Bekaert et al. (2007) report average incidence of zero daily returns that range from 8% for Korea to 52% for Colombia.

[20] We use 15% trimming in this paper.

Table 7
The effects of *PSZ* 3–9741 on momentum returns.

The momentum portfolios are formed based on six-month lagged returns and held for six months. The stocks are ranked in ascending order on the basis of the lagged returns. An equally weighted portfolio of stocks in the lowest past return tercile is the sell portfolio, and an equally weighted portfolio of the stocks in the highest return tercile is the buy portfolio. This table presents tests of the differences in average momentum returns before and after *PSZ* 3–9741, a Russian law dated June 8, 1893. The law removed all restrictions that prohibited futures dealings in stocks. These dealings are defined as any purchase of stock in the absence of cash and with delivery at a certain time in the future. The momentum portfolios in Panel A are formed using stocks listed on the St. Petersburg Stock Exchange from February 1865 to July 1914. The momentum portfolios in Panel B are formed using stocks listed on the London Stock Exchange from August 1866 to December 1907. The results in the last row of each panel are obtained by regressing on a dummy variable that is one if the month is on or after June 1893, and zero otherwise, and a trend variable. *t*-statistics are in parentheses. The sample period is January 1865 to July 1914.

	Winners (W)	Losers (L)	W-L
Panel A: Momentum in Russia (2/1865–7/1914)			
Pre-1893: 2/1865–5/1893	0.0065	0.0056	0.0005
	(3.87)	(3.30)	(0.33)
Post-1893: 6/1893–7/1914	0.0089	0.0006	0.0083
	(3.56)	(0.26)	(5.41)
Post-1893 minus pre-1893	0.0025	−0.0049	0.0078
	(0.84)	(−1.70)	(3.51)
Post-1893 minus pre-1893 controlling for trend	0.0114	−0.0033	0.0139
	(2.01)	(−0.57)	(3.22)
Panel B: Momentum in Britain (8/1866–12/1907)			
Pre-1893: 8/1866–5/1893			0.0036
			(2.54)
Post-1893: 6/1893–12/1907			0.0034
			(1.73)
Post-1893 minus pre-1893			−0.0002
			(−0.07)
Post-1893 minus pre-1893 controlling for trend			−0.0013
			(−0.30)

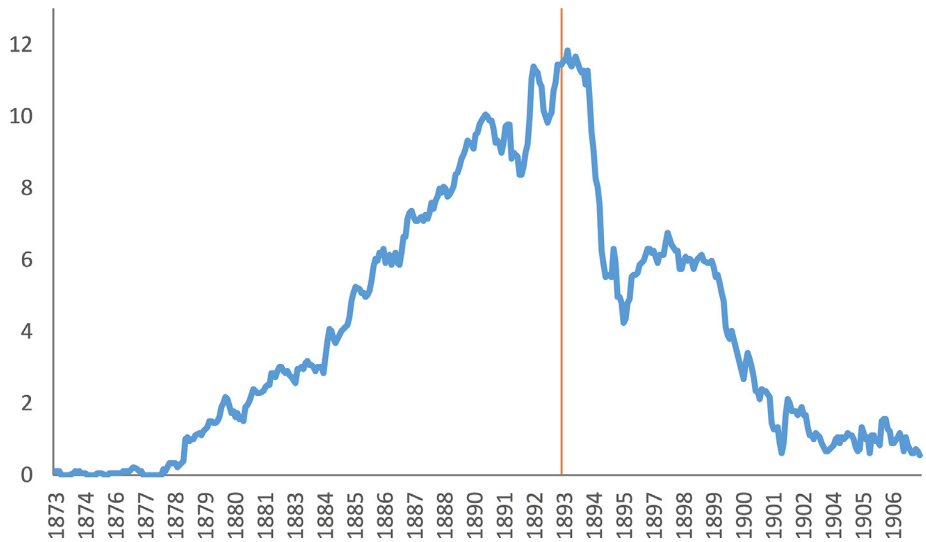

Fig. 3. Chow (1960) *F*-statistics. The momentum portfolios are formed based on six-month lagged returns and held for six months. The stocks are ranked in ascending order on the basis of the lagged returns. An equally weighted portfolio of stocks in the lowest past return tercile is the sell portfolio, and an equally weighted portfolio of the stocks in the highest return tercile is the buy portfolio. This figure shows Chow (1960) *F*-statistics for structural breaks in the average return of the zero-cost, buy minus sell, portfolio between the first and last 15% of the sample period. The vertical line indicates the month of June 1893. *F*-statistics are computed using heteroskedasticity-and-autocorrelation-consistent covariance matrices of Andrews (1991). The sample period is January 1865 to July 1914.

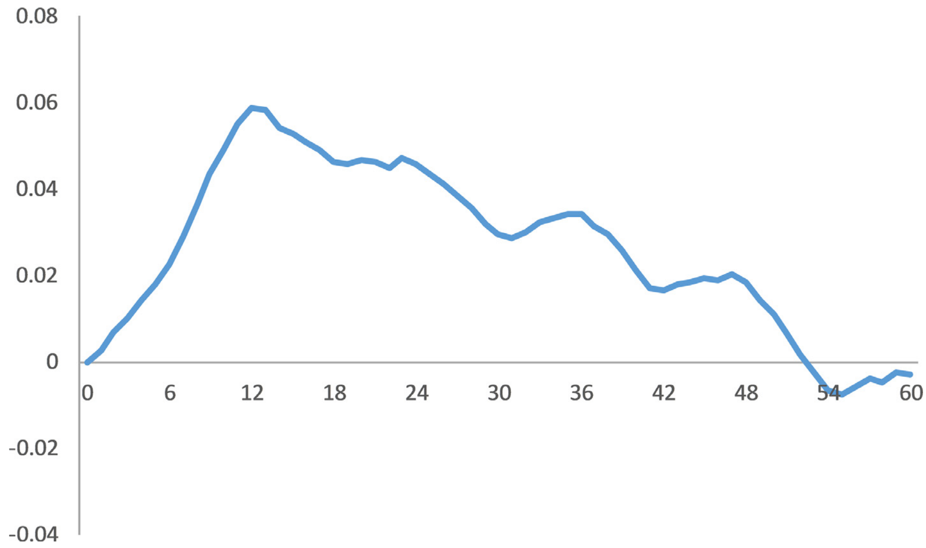

Fig. 4. Cumulative momentum profits in event time. The momentum portfolios are formed based on six-month lagged returns. The stocks are ranked in ascending order on the basis of the lagged returns. An equally weighted portfolio of stocks in the lowest past return tercile is the sell portfolio, and an equally weighted portfolio of the stocks in the highest return tercile is the buy portfolio.This figure shows the average cumulative return to the zero-cost, buy minus sell, portfolio in the 60 months following portfolio formation. The sample period is January 1865 to July 1914.

break in the momentum effect occurred around the time *PSZ* 3–9741 was enacted.[21]

Panel B of Table 7 presents the results of a placebo test that we conducted using momentum returns from Britain over the period August 1866 to December 1892.[22] Britain did not undergo a similar regulatory regime change as Russia did in 1893; thus, we should not detect a significant difference in average momentum returns between the pre-1893 period and the post-1893 period in Britain. We see that this is indeed the case—the difference is two basis points and not statistically significant. A difference-in-differences test between the momentum returns in the last row of Panel A and Panel B yields an estimate of 1.52% with a t-statistic of 2.49. Taken together, our results are largely consistent with behavioral theories of momentum.

4.4. Momentum strategies in event time

We can broadly divide behavioral explanations of momentum into two categories. De Long et al. (1990), Daniel et al. (1998), and Barberis and Shleifer (2003) argue that momentum is the result of overreaction to information by market participants. As an example, the Daniel-Hirshleifer-Subrahmanyam model assumes a representative investor who is overconfident about the precision of his private signal. New public signals, on average, are viewed as confirming the validity of the investorâs private signal. Thus, public information triggers further overreaction to a preceding private signal. This continuing overreaction causes momentum in security prices.

Meanwhile, Barberis et al. (1998), Hong and Stein (1999), and Grinblatt and Han (2005) propose investor underreaction to news as an explanation. For instance, in the Hong-Stein model, two groups of boundedly rational agents interact when information diffuses gradually across the population. Prices underreact in the short run, so momentum trading is profitable.

To differentiate between over- and underreaction theories, we can examine the cumulative returns of the momentum portfolio following the initial formation date. The two sets of theories make diametrically opposed predictions. On the one hand, overreaction theories predict that the momentum profits accrued over the initial holding period will eventually be reversed. On the other hand, underreaction theories predict that some of the accrued profits will remain.

Specifically, we calculate the average cumulative returns on buying past winners and selling past losers in the hth month after the strategy is put into place. Fig. 4 illustrates our results as we let h vary from 1 to 60. It reveals a clear pattern of momentum and reversal. The profits increase monotonically until they reach about 6% at the end of month 12. Then, over the next 48 months, roughly all of the accrued profits are dissipated. Starting in month 42, the average cumulative return is not distinguishable from zero. These results are remarkably similar to those of earlier studies using U.S. data.[23] They are consistent with

[21] We also run a Quandt–Andrews test on the liquidity measure. Because the measure has a significant trend (while momentum return does not), the appropriate null hypothesis in this case is constancy of the intercept and the trend coefficient against the alternative of a significant break of unknown timing. We obtain a *supF*-statistic of 68.79 with a p-value of less than 0.01.

[22] We thank Ben Chabot for providing this data.

[23] See, e.g., Fig. 3 of Jegadeesh and Titman (2001).

Table 8
Returns of price-based momentum portfolios.

The momentum portfolios are formed based on *J*-month lagged returns and held for *K* months. The stocks are ranked in ascending order on the basis of the lagged returns. An equally weighted portfolio of stocks in the lowest past return tercile is the sell portfolio, and an equally weighted portfolio of the stocks in the highest return tercile is the buy portfolio. This table presents the average monthly returns of these portfolios, formed using two price-based subsamples of stocks. The values of *J* and *K* for the different strategies are indicated in the first column and row, respectively. Panel A and Panel B present, respectively, the momentum portfolios formed using the low-price subsample and the high-price subsample. *t*-statistics are in parentheses. The sample period is January 1865 to July 1914.

		Panel A: Low price					Panel B: High price				
	J	*K*=	3	6	9	12	*K*=	3	6	9	12
3	Buy		0.0081	0.0083	0.0085	0.0084		0.0044	0.0050	0.0053	0.0053
			(4.79)	(4.95)	(5.28)	(5.23)		(2.92)	(3.43)	(3.93)	(3.99)
	Sell		0.0038	0.0047	0.0047	0.0042		0.0030	0.0035	0.0037	0.0032
			(2.01)	(2.59)	(2.70)	(2.57)		(2.02)	(2.68)	(2.90)	(2.53)
	Buy minus sell		0.0044	0.0036	0.0037	0.0042		0.0015	0.0013	0.0017	0.0020
			(2.79)	(2.82)	(3.38)	(4.41)		(1.18)	(1.31)	(1.99)	(2.68)
6	Buy		0.0074	0.0081	0.0091	0.0088		0.0055	0.0061	0.0063	0.0061
			(4.13)	(4.77)	(5.45)	(5.24)		(3.33)	(3.93)	(4.38)	(4.30)
	Sell		0.0024	0.0032	0.0025	0.0021		0.0030	0.0029	0.0027	0.0029
			(1.32)	(1.70)	(1.46)	(1.33)		(2.25)	(2.22)	(2.11)	(2.18)
	Buy minus sell		0.0047	0.0044	0.0060	0.0060		0.0025	0.0030	0.0035	0.0030
			(2.72)	(2.82)	(4.34)	(4.84)		(1.77)	(2.43)	(3.52)	(3.29)
9	Buy		0.0083	0.0092	0.0098	0.0094		0.0062	0.0067	0.0063	0.0059
			(4.67)	(5.25)	(5.63)	(5.42)		(3.89)	(4.48)	(4.32)	(4.18)
	Sell		0.0023	0.0019	0.0019	0.0022		0.0031	0.0028	0.0030	0.0033
			(1.09)	(1.01)	(1.12)	(1.32)		(2.26)	(2.06)	(2.29)	(2.50)
	Buy minus sell		0.0057	0.0069	0.0074	0.0067		0.0026	0.0034	0.0033	0.0027
			(2.93)	(4.20)	(4.97)	(4.86)		(1.99)	(2.70)	(2.85)	(2.45)
12	Buy		0.0092	0.0091	0.0099	0.0093		0.0063	0.0066	0.0063	0.0058
			(5.09)	(5.22)	(5.64)	(5.33)		(3.92)	(4.27)	(4.22)	(4.00)
	Sell		−0.0004	0.0013	0.0018	0.0025		0.0026	0.0029	0.0031	0.0039
			(−0.20)	(0.72)	(1.04)	(1.47)		(1.90)	(2.12)	(2.29)	(2.88)
	Buy minus sell		0.0095	0.0075	0.0075	0.0063		0.0037	0.0033	0.0031	0.0018
			(5.11)	(4.54)	(4.81)	(4.29)		(2.64)	(2.47)	(2.48)	(1.52)

overreaction theories and inconsistent with underreaction theories.[24]

4.5. Subsample analysis

Jegadeesh and Titman (1993) measure momentum profits on size-based subsamples to examine whether the profitability of the strategy is confined to any particular subsample of stocks. Subsequently, researchers generally find that momentum profits decrease with firm size, consistent with prediction from behavioral theories. The idea is that information tends to be more uncertain for small stocks, and they tend to attract less sophisticated investors. (Hong et al., 2000; Zhang, 2006). Again, we use price to proxy for size and present average returns of the momentum portfolios for two price-based subsamples in Table 8. We find that momentum profits in the high-price subsample are all lower and less statistically significant than in the low-price subsample. For the strategy in which $(J, K) = (12, 3)$, the average return is 95 basis points with a *t*-statistic of 5.11 in the low-price subsample, and 37 basis points with a *t*-statistic of 2.64 in the high-price subsample.

Jegadeesh and Titman (1993) also find that the momentum strategy incurs significant losses in January but achieves positive abnormal returns in the other months. Grinblatt and Moskowitz (2004) study this seasonality carefully and attribute it to tax-loss selling. Because the Russian government did not tax capital gains, we can perform a placebo test for the tax-loss selling hypothesis using our sample. Table 9 provides the average return of the momentum strategy for each month of the year. While the strategy on average loses 39 basis points in each January, it achieves statistically significant average monthly profits of 47 basis points in the other months. Consistent with earlier papers, we find the negative January performance of the momentum strategy to be driven by small firms. We conduct *F*-tests for the null hypothesis that momentum profits in January are equal to those in other calendar months. The *p*-values are 0.03 for the full sample and 0.01 for low-price stocks, indicating a significant January seasonal. Hence, our results are not consistent with the tax-loss selling hypothesis.

[24] They are also inconsistent with a class of risk-based models that attribute the momentum effect to cross-sectional variation in expected returns. According to these models, past winners should outperform past losers in any period after portfolio formation. See, e.g., Conrad and Kaul (1998).

Table 9
Momentum returns by calendar months.
The momentum portfolios are formed based on six-month lagged returns and held for six months. The stocks are ranked in ascending order on the basis of the lagged returns. An equally weighted portfolio of stocks in the lowest past return tercile is the sell portfolio, and an equally weighted portfolio of the stocks in the highest return tercile is the buy portfolio. This table presents the average returns of the zero-cost, buy minus sell, portfolio by calendar months. *t*-statistics are in parentheses. The *F*-statistics are computed under the hypothesis that the mean return in January is equal to the mean return in February through December. *p*-values are in brackets. The sample period is January 1865 to July 1914.

	All stocks	Low price	High price
Jan.	−0.0039	−0.0091	0.0008
	(−0.94)	(−1.14)	(0.17)
Feb.	−0.0002	0.0045	−0.0040
	(−0.07)	(0.62)	(−1.09)
Mar.	0.0003	−0.0042	0.0019
	(0.07)	(−0.87)	(0.50)
Apr.	0.0029	0.0063	0.0007
	(0.84)	(1.37)	(0.17)
May	0.0012	0.0040	−0.0013
	(0.29)	(0.81)	(−0.28)
Jun.	0.0042	0.0023	0.0001
	(1.13)	(0.49)	(0.02)
Jul.	0.0140	0.0134	0.0146
	(3.44)	(2.75)	(3.29)
Aug.	0.0062	0.0044	0.0060
	(2.36)	(1.30)	(2.03)
Sep.	0.0056	0.0054	0.0058
	(1.25)	(0.94)	(2.07)
Oct.	0.0055	0.0085	0.0040
	(1.66)	(1.72)	(1.29)
Nov.	0.0057	0.0079	0.0039
	(1.26)	(1.50)	(0.55)
Dec.	0.0062	0.0101	0.0034
	(2.01)	(1.94)	(0.86)
Feb.-Dec.	0.0047	0.0056	0.0032
	(4.06)	(3.65)	(2.51)
F-stat?	4.65	6.72	0.30
	[0.03]	[0.01]	[0.59]

5. Conclusion

In this paper, we demonstrate momentum profitability in a novel, untouched sample. The setting of our experiment—the 19th century St. Petersburg Stock Exchange —has some unique features: the absence of a delegated management structure, the lack of an extreme momentum crash despite considerable variation in macroeconomic and political conditions, and most importantly, the occurrence of an exogenous shock to market composition. We try to distinguish between theories of momentum that have received attention in the academic literature: the institutional theory, risk-based theories, and behavioral theories. Our evidence is supportive of behavioral theories that attribute momentum profits to investor overreaction.

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