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Market Behavior in the Face of Political Violence: Evidence from Tsarist Russia

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Abstract: Even efficient financial markets may break down under periods of prolonged stress, especially when the ramification of an event is unclear. Political violence is such an event, sending immediate signals about possible impact on firm valuations but unclear information about the future viability of existing institutions. This paper examines the effect of political violence in 19th century Russia on its stock market; using a battery of unit root and variance ratio tests, the evidence is that Russian financial markets were mostly efficient in processing short-term information from political violence. However, when violence was at its peak between the assassination of the Tsar in 1881 and the 1905 revolution, large deviations from efficiency can be detected, as markets were unsure about the viability of the existing rules of the game.

Keywords: political violence; efficient markets; institutions

JEL Classification: G14; N23; D74; P48



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1. Introduction

Financial markets have been shown to recognize the “black swan” nature of political violence, especially terrorism, and discount their occurrence appropriately (Mnasri and Nechi 2016). Indeed, effective and efficient financial markets could absorb the information contained in political instability quickly and, in the best-case scenario, could actually act as providers of information to other institutional actors on these ramifications (Bond et al. 2012).

However, even the most efficient markets can be stressed and in times of crises, interruptions to efficiency may occur (Anagnostidis et al. 2016; Aktan et al. 2019), especially in an environment where the informational content of an event is uncertain. Political violence represents such a form of stress on financial markets, as these events often do not offer precise and actionable information about the longer-term ramifications of instability. While financial markets may be incredibly efficient in the short-term in absorbing the information provided by political violence, they can remain uncertain about its future effects and prone to mispricing or distortions if the ramifications cannot be adequately ascertained. Additionally, the cumulative effect of additional instability may call into question the health of the entire institutional system of a country, with withdrawal or reallocation of portfolios a rational response to perceived continued instability.

This paper examines this question in the context of 19th century Russia, which offers an environment of repeated stress to test just what effect political volatility had on financial markets. Tsarist Russia had strong financial institutions (Ukhov 2003) but weak political institutions, with little political development or participation beyond the Tsar and his family. This reality led to sustained political violence from 1866 onward, including the assassination of the Tsar in 1881, rising to a crescendo before and after the revolution of 1905: estimates of the number killed in political violence in the first decade of the 20th century run into the tens of thousands (Geifman 1995). Using monthly data from the

St. Petersburg Stock Exchange juxtaposed with a unique database on political violence (Hartwell 2020), this paper explores the efficiency of Russian equity markets under this form of stress. The results show that Russian markets performed efficiently in the face of most political violence, in line with and not dissimilar from modern capital markets (Goel et al. 2017). However, in the decades of highest violence and particularly in the years surrounding the 1905 Revolution, the market showed signs of stress, as the outcome of the violence was anything but clear.

2. Methodology

With a dearth of information available on market conditions beyond returns in Tsarist Russia, it is difficult to test for all impediments to market efficiency that may have been present surrounding the St. Petersburg Stock Exchange, such as capacity constraints or operational inefficiencies (Karolyi 2015). At the same time, a lack of digital resources for daily data during the Tsarist era means that other direct tests, such as event studies, which could uncover abnormal returns and/or behavior, are much more difficult to undertake. However, it is possible to observe overall market behavior using an index series, as the presence of a unit root implies that a time series is either a random walk or a random walk with drift (as shown in Lee et al. (2010) and Lim and Brooks (2011)). As a corollary to this assumption, returns series from an index should result in stationarity, implying efficiency (but not necessarily forming a necessary or sufficient condition to definitively state if a market is efficient, see Campbell et al. (1997)). Indeed, the presence of stationarity in a returns series may not conclusively prove market “efficiency”, in the sense of market rationality; however, the presence of mean reversion or dependence does suggest that markets are mispricing capital or risk, with temporary shocks to returns overwhelming longer-term price discovery mechanisms (Worthington and Higgs 2009).

This approach to understanding market behavior may be preferable to examining abnormal returns over a longer period, as abnormal returns imply that there is a “normal” expected rate of return—a difficult exercise when examining 50 years of data, widely varying rates of the time value of money and rapid changes in the structure and development of a country’s economy. Thus, the agnostic approach of unit root testing may capture mean reversion, based on the path of the data rather than an arbitrary expected return.

Market index information from the St. Petersburg Stock Exchange (SPSE) is available on monthly basis back to 1865, obtained from Goetzmann and Huang (2018). As is standard in the financial literature, broad market index returns are taken as a proxy for financial responses, with monthly returns calculated here as:

$$R_t = \log\left(\frac{P_t}{P_{t-1}}\right) \quad (1)$$

The path of both the index and the returns series is shown in Figure 1.

To test the Russian market’s behavior over this 50-year period, a series of (linear) standard unit root tests may be used, namely Augmented Dickey–Fuller (ADF), Phillips–Perron (PP), Elliot–Rothenberg–Stock (ERS) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS). Additionally, given research which shows that series which have a structural break may lead to under-rejection of the null hypothesis of a unit root (see Lim and Brooks 2011), unit root tests allowing for structural breaks in both additive and innovation outliers are utilized (along the lines of Zivot and Andrews (2002) and Perron (2006)). Such a break can be seen in Figure 1 occurring at the beginning of the 20th century, as the Russian stock market underwent a financial crisis starting in March 1899, bottoming out in January 1901 and, thus, these additional unit root tests are crucial to capture this regime shift.

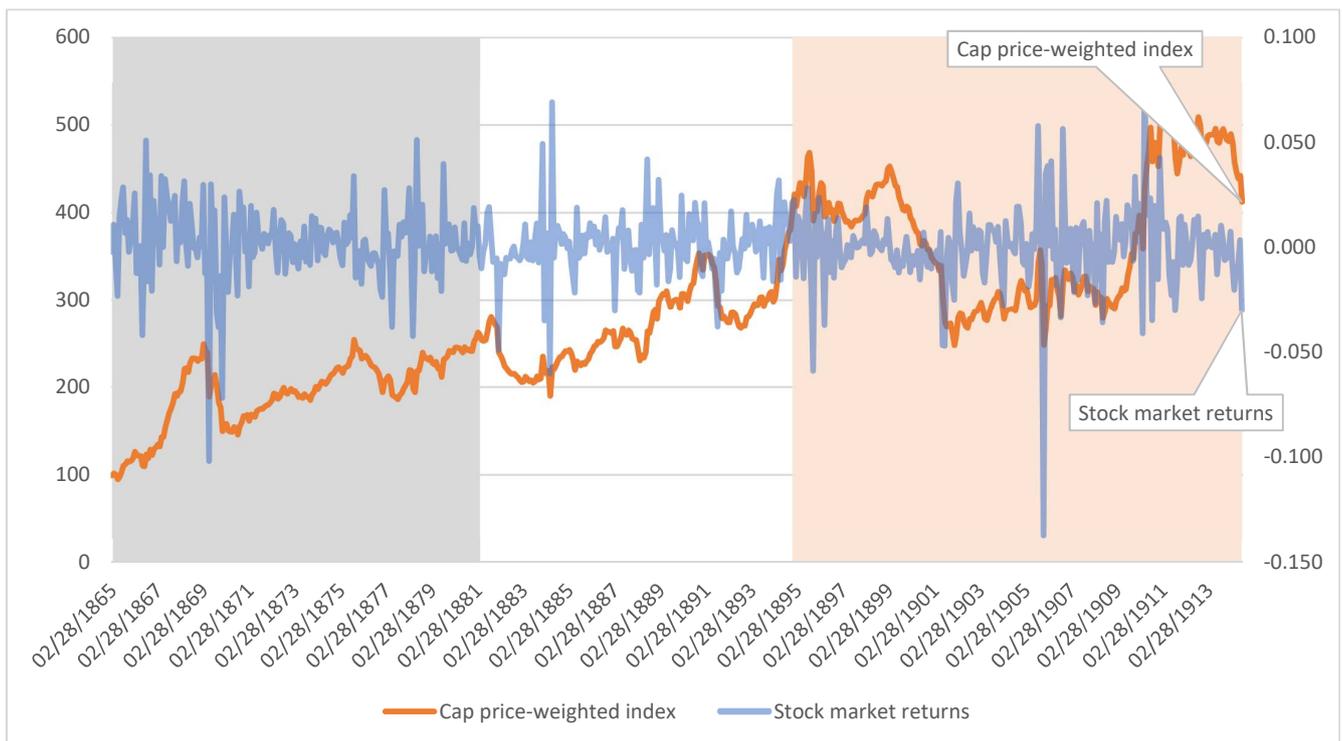


Figure 1. Monthly Log Returns in the St. Petersburg Stock Exchange versus the Index Data. *Source:* Author’s calculations from Goetzmann and Huang (2018) data. Shaded areas indicate reign by Tsar: Alexander II (1865–1881), Alexander III (1881–1894) and Nicholas II (1894–1914).

Linear unit root tests are only a first approximation for understanding mean reversion behavior, however, and additional tests prevalent in the finance literature are also used here to explore how Russian financial markets behaved in the face of political violence. In particular, variance ratio (VR) tests are popular for examining market efficiency, generating a ratio of stock price change variance across time periods which should be equal to 1 in the presence of a random walk:

$$VR(q) = \frac{\left(\frac{1}{q}\right)Var(p_t - p_{t-q})}{Var(p_t - p_{t-1})} = \frac{\delta^2(q)}{\delta^2(1)} = 1 + 2 \sum_{k=1}^{q-1} \left(1 - \frac{k}{q}\right) \hat{\rho}(k) \tag{2}$$

where the variance ratio (VR) is measured as the ratio of the variance (δ) of the q -th period versus the variance in period 1, also shown as a function of an autocorrelation function ($\hat{\rho}$) of lag k . This individual VR test is used to compare two periods and is due to Lo and MacKinlay (1989), who also provide a test statistic to measure how significant the distance of a calculated VR of a series is from 1 based on either an assumption of homoskedasticity (test statistic Z_1) or heteroskedasticity (test statistic Z_2) in the series (significance equating to correlation of prices with previous periods). A similar, but more powerful, test based on the Lo and MacKinlay approach comes from Chow and Denning (1993) who allow for multiple VR tests across time and generates a test statistic which controls for the multiple periods; as with Lo and MacKinlay, a significant test statistic implies non-efficiency.¹ For this examination, we utilize Lo and MacKinlay VR test assuming heteroskedasticity, the Chow–Denning joint test and the approach of Kim (2006), which utilizes a wild bootstrap to improve the small sample properties of both tests.

Finally, and most importantly, even if an entire series linearly can be described as non-stationary, there may be periods of stationarity because of non-linearity. This reality can be captured using nonlinear unit root tests such as those designed by Kapetanios et al. (2003, hereafter KSS) and Kapetanios and Shin (2008, hereafter KS), which test a null hypothesis

of a unit root against the alternative of a globally stationary exponential smooth transition autoregressive (ESTAR) process. The KSS approach models the market index as

$$\Delta y_t = \gamma y_{t-1} \left\{ 1 - \exp\left(-\theta y_{t-1}^2\right) \right\} + \varepsilon_t \tag{3}$$

where y is the demeaned or detrended time series of the index, γ is an unknown parameter which is modeled as a first-order Taylor series approximation of θ and the error term is stochastic and assumed to have zero mean, constant variance and be normally distributed. The middle term in Equation (3) is an exponential transition function included to capture the nonlinearities of the data. The KSS approach demeans or de-trends the data using an OLS-based procedure, while the innovation of the KS approach is to instead use a GLS de-trending (de-meaning) procedure.

As shown in Aktan et al. (2019, p. 991), the presence of ESTAR stationarity indicates that markets—and especially emerging markets—have “market frictions and transaction costs . . . provid[ing] grounds for arbitrage opportunities.” Thus, while there may be overall efficiency, in the presence of crises or other stresses on the system (as Aktan et al. (2019) make clear), there may be episodes where uncertainty prevails, and mispricing can occur. This is a key point when understanding the effects of political violence in a weaker institutional system, where the informational content of terrorism or political violence is not evident; that is, political violence and the uncertainty it causes can stress even the most efficient of markets, but in an environment without strong supporting institutions and where the overall political environment is fragile, the effects on market behavior may be amplified.

3. Results

As described above, a weak-form efficient market will have non-stationarity in its levels but returns should be stationary. This effect is precisely what is shown in the results as displayed in Tables 1 and 2, as there is a clear indication of a unit root in the stock market levels but stationarity in returns. Across the ADF, PP and ERS tests (Table 1), including both drift and intercept, intercept alone and with no drift, the null of non-stationarity cannot be rejected for the index levels, while the null is rejected soundly for returns.² Similarly, in the KPSS test, which has a null of stationarity, the results are reversed, with the index series rejecting the null and returns not rejecting the null. In any event, all of these tests point to a non-stationary index series and a stationary returns series, making the St. Petersburg Stock Exchange both I(1) and, in some sense, weak form efficient in processing information. These results hold in Table 2, where we correct for the structural breaks in the series (which the tests confirm occur sometime around 1900, as seen in Figure 1). No matter which outlier is tested for (additive or innovation), the null of a unit root cannot be rejected for the index series but is definitively rejected for the stock market returns.

Table 1. Unit root tests on stock index levels and returns.

Test	ADF		PP		ERS		KPSS	
Null Hypothesis	H0: Non-Stationary		H0: Non-Stationary		H0: Non-Stationary		H0: Stationary	
	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept
Index series	−1.342	−2.466	−1.331	−2.470	47.123	9.374	2.405	0.244
<i>p</i> -values	0.611	0.345	0.616	0.354	1.000	0.500	0.000 ***	0.000 ***
Returns	−22.110	−22.090	−22.070	−22.050	0.108	0.356	0.059	0.059
<i>p</i> -values	0.000 ***	0.000 ***	0.000 ***	0.000 ***	0.000 ***	0.000 ***	0.137	0.813

Note: ADF is the Augmented Dickey–Fuller test, PP is the Phillips–Peron test, ERS is the Elliot–Rothenberg–Stock Point Optimal test and KPSS is the Kwiatkowski–Phillips–Schmidt–Shin test. ***, ** and * for *p*-values denote significance at the 1%, 5% and 10% levels, respectively. Sample period is for the entire sample, January 1865–July 1914.

Table 2. Unit root tests on stock index levels and returns including structural breaks.

	Variable	Trend and Intercept/Trend	Trend and Intercept/Intercept	Trend Intercept/Trend and Intercept
Innovation Outlier	Index Series	−2.7573	−4.097	−4.14
<i>p</i> -values		0.8206	0.3143	0.4322
Innovation Outlier	Returns	−22.28	−24.41	−24.34
<i>p</i> -values		0.000 ***	0.000 ***	0.000 ***
Additive Outlier	Index Series	−2.88	−4.44	−4.15
<i>p</i> -values		0.6588	0.1528	0.423
Additive Outlier	Returns	−22.39	−24.46	−24.32
<i>p</i> -values		0.000 ***	0.000 ***	0.000 ***

***, ** and * for *p*-values denote significance at the 1%, 5% and 10% levels, respectively. Sample period is for the entire sample, January 1865–July 1914.

Going deeper into possible measures of market behavior, the variance ratio tests noted above have the opposite null from the majority of the unit root tests, with the null hypothesis that the index series is a martingale (i.e., that it displays some attributes of weak form efficiency). As the results in Table 3 show across all of the VR tests, the null cannot be rejected for both the Lo and MacKinley individual tests and the Chow–Denning test. This result holds under the Kim (2006) wild bootstrap, as coefficients and *p*-values all are comfortably distant from rejecting the null of a martingale.

Table 3. Variance ratio tests on stock index level.

H0: Index Is a Martingale			
Individual (Lo and MacKinlay)	V(k)	Z-Statistic	<i>p</i> -Value
Asymptotic normal			
2	1.067	0.794608	0.4268
4	0.978	−0.147202	0.883
8	0.881	−0.5078	0.6116
16	1.130	0.39277	0.6945
Wild Bootstrap (Kim 2006)			
2	1.067	0.795	0.440
4	0.978	−0.147	0.885
8	0.881	−0.508	0.642
16	1.130	0.393	0.688
Joint (Chow and Denning)			
	Max V(k)	Max z-statistic	<i>p</i> -value
Asymptotic normal			
	1.07	0.794608	0.8291
Wild Bootstrap (Kim 2006)			
	1.07	0.794608	0.744

Tests run at periods 2: 4, 8 and 16 individually and then jointly for the Chow and Denning Test. Wild bootstrap with 1000 repetitions, two-point distribution and Knuth random generator.

However, while markets may be efficient overall, they can be prone to specific episodes of inefficiency when under stress (Aktan et al. 2019), a key issue for a country undergoing paroxysms of violence and political unrest. The results of the KSS and KS tests are shown in Table 4 and lend credibility to this interpretation: in three out of the four specifications noted, the null of a unit root is rejected in favor of a stationary ESTAR, meaning that the whole market returns were mean-reverting and not actually a random walk. Thus, while linear and less powerful non-linear tests suggest that the Russian stock market in the 19th century was efficient, the KSS and KS tests appear to suggest otherwise.

Table 4. Non-linear unit root tests on stock index levels.

Kapetanios et al. (2003)-OLS			
de-meaned			
<i>Criteria</i>	<i>Lags</i>	<i>KSS stat.</i>	<i>p-Value</i>
FIXED	18	−2.525	0.031 **
AIC	14	−2.532	0.044 **
SIC	0	−2.126	0.141
GTS05	13	−2.476	0.09 *
GTS10	14	−2.532	0.061 *
de-trended			
<i>Criteria</i>	<i>Lags</i>	<i>KSS stat.</i>	<i>p-Value</i>
FIXED	18	−4.47	0.000 ***
AIC	14	−4.499	0.000 ***
SIC	0	−3.961	0.000 ***
GTS05	13	−4.587	0.000 ***
GTS10	14	−4.499	0.000 ***
Kapetanios and Shin (2008)-GLS			
de-meaned			
<i>Criteria</i>	<i>Lags</i>	<i>KS stat.</i>	<i>p-Value</i>
FIXED	18	−0.326	0.632
AIC	14	−0.348	0.694
SIC	0	0.14	0.832
GTS05	13	−0.475	0.699
GTS10	14	−0.348	0.723
de-trended			
<i>Criteria</i>	<i>Lags</i>	<i>KS stat.</i>	<i>p-Value</i>
FIXED	18	−3.325	0.002 ***
AIC	14	−3.339	0.004 ***
SIC	0	−2.741	0.022 ***
GTS05	11	−3.798	0.001 ***
GTS10	13	−3.551	0.002 ***

Note: *p*-values for tests shown under the null of a unit root and the alternative of a stationary nonlinear ESTAR model. ***, ** and * for *p*-values denote significance at the 1%, 5% and 10% levels, respectively. Fixed: fixed lag length chosen by Schwert (1989) maximum. AIC = Akaike Information Criterion. SIC: Schwarz Information Criterion. GTS05 and GTS10: General to specific algorithm with significance level set at 5% or 10%, respectively. See Otero and Smith (2017). Sample period is for the entire sample, January 1865–July 1914.

It is when we unpack this result to see its driver that we can understand the effects of political violence, as Table 5 shows the results of KS and KSS tests applied to each decade of returns in Tsarist Russia. The key takeaway here is that the inefficiencies occur within the decade of 1890 to 1899, i.e., the decade where political violence began to erupt (Figure 2) and where pre-existing financial stresses were also accumulating. During 1890 to 1899, the KS and KSS tests show highly significant deviations from a random walk, coinciding with the surge in violence from 1890 to 1894 (see Hartwell 2020) and continuing from the unrest started by the assassination of the Tsar in 1881. This period also contains the beginning of the financial crisis in Russia which erupted in 1899, but the fact that the bulk of the crisis

impacted the economy only in the early 20th century perhaps discounts the crisis as an explainer for the behavior of markets in this decade.

Table 5. Non-linear unit root tests by decade on stock index levels.

Kapetanios et al. (2003)				Kapetanios and Shin (2008)		
<i>1866–1869</i>						
de-trended						
Criteria	Lags	KSS stat.	<i>p</i> -Value	Lags	KS stat.	<i>p</i> -Value
FIXED	9	−0.107	0.976	9	−1.376	0.662
AIC	0	1.846	1.00	7	−1.81	0.573
SIC	0	1.846	1.00	0	−0.02	0.997
GTS05	0	1.846	1.00	7	−1.81	0.563
GTS10	7	−0.348	0.971	7	−1.81	0.571
<i>1870–1879</i>						
Criteria	Lags	KSS stat.	<i>p</i> -Value	Lags	KS stat.	<i>p</i> -Value
FIXED	12	−2.768	0.063	12	−2.432	0.08
AIC	0	−1.901	0.509	0	−1.665	0.541
SIC	0	−1.901	0.471	0	−1.665	0.518
GTS05	0	−1.901	0.56	0	−1.665	0.602
GTS10	11	−2.52	0.203	0	−1.665	0.583
<i>1880–1889</i>						
Criteria	Lags	KSS stat.	<i>p</i> -Value	Lags	KS stat.	<i>p</i> -Value
FIXED	12	−3.121	0.025 **	12	−2.121	0.162
AIC	8	−3.038	0.063 *	8	−2.101	0.275
SIC	1	−2.072	0.362	1	−1.349	0.733
GTS05	3	−2.664	0.162	1	−1.349	0.784
GTS10	8	−3.038	0.065 *	8	−2.101	0.306
<i>1890–1899</i>						
Criteria	Lags	KSS stat.	<i>p</i> -Value	Lags	KS stat.	<i>p</i> -Value
FIXED	12	−4.113	0.001 ***	12	−3.835	0.001 ***
AIC	12	−4.113	0.003 ***	4	−2.625	0.098 *
SIC	0	−2.83	0.082 *	0	−2.717	0.067 *
GTS05	11	−3.737	0.01 ***	11	−3.464	0.014 **
GTS10	12	−4.113	0.003 ***	12	−3.835	0.004 ***
<i>1900–1909</i>						
Criteria	Lags	KSS stat.	<i>p</i> -Value	Lags	KS stat.	<i>p</i> -Value
FIXED	12	−2.846	0.052 *	12	−1.49	0.51
AIC	3	−1.881	0.522	3	−0.796	0.951
SIC	0	−2.2	0.291	0	−1.304	0.76
GTS05	9	−2.534	0.21	9	−1.285	0.816
GTS10	11	−2.828	0.106	9	−1.285	0.805

Table 5. Cont.

Kapetanios et al. (2003)				Kapetanios and Shin (2008)		
1903–1905						
Criteria	Lags	KSS stat.	p-Value	Lags	KS stat.	p-Value
FIXED	9	−1.412	0.60	9	−1.355	0.655
AIC	1	−4.512	0.004 ***	1	−4.475	0.004 ***
SIC	1	−4.512	0.003 ***	1	−4.475	0.003 ***
GTS05	1	−4.512	0.003 ***	1	−4.475	0.003 ***
GTS10	6	−2.403	0.271	6	−2.362	0.283
1910–1914						
Criteria	Lags	KSS stat.	p-Value	Lags	KS stat.	p-Value
FIXED	8	−0.061	0.924	8	−0.122	0.952
AIC	7	−0.656	0.936	7	−0.687	0.969
SIC	7	−0.656	0.924	7	−0.687	0.965
GTS05	0	−0.472	0.951	0	−0.495	0.977
GTS10	7	−0.656	0.916	7	−0.687	0.954

Note: p-values for tests shown under the null of a unit root and the alternative of a stationary nonlinear ESTAR model. ***, ** and * for p-values denote significance at the 1%, 5% and 10% levels respectively. Fixed: fixed lag length chosen by Schwert (1989) maximum. AIC = Akaike Information Criterion. SIC: Schwarz Information Criterion. GTS05 and GTS10: General to specific algorithm with significance level set at 5% or 10%, respectively. See Otero and Smith (2017).

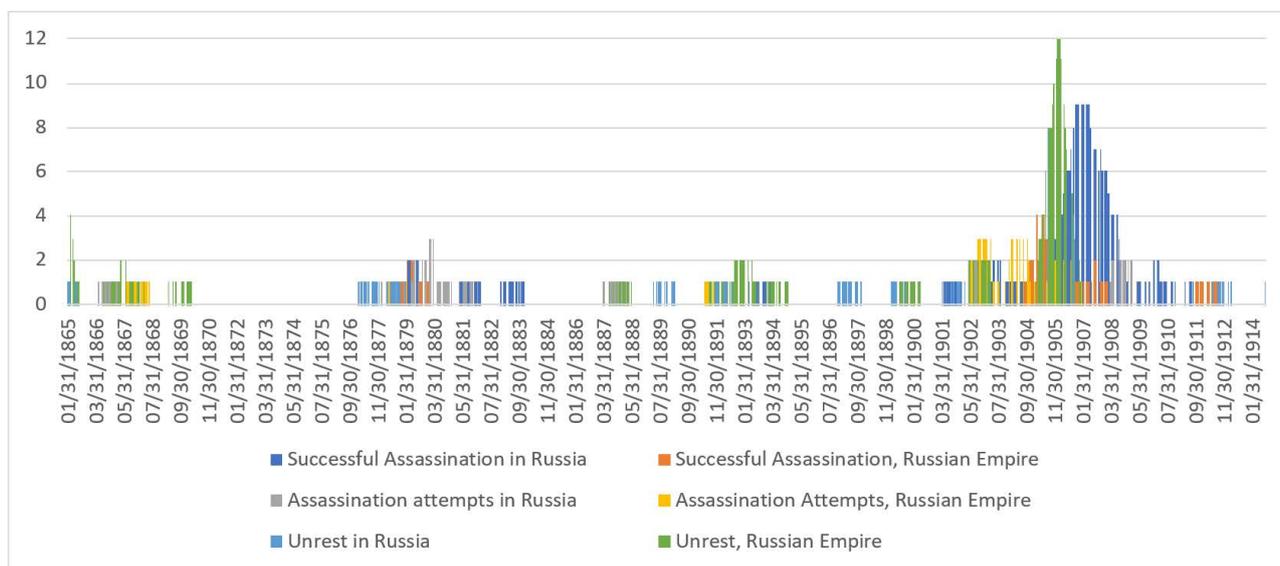


Figure 2. Months within the past year with an event of political violence. Note: Bars show the number of months in the year preceding a particular month in which at least one episode of that type of political violence occurred (meaning a minimum of 0 if no violence occurred to a maximum of 12 if at least one act occurred in each month of the preceding year). Political violence broken out by assassination attempts, successful assassinations and unrest (collective violence) in both Russia proper and in the Russian Empire only (Ukraine, the Caucasus, conquered Poland and the Baltic States). More detail available at Hartwell (2020).

Perhaps more interestingly is looking closer around the events surrounding the Revolution of 1905, where approximately 20,000 people were killed over the course of the entire year (Clodfelter 2017) and where there was little sense of the end result, how it would impact Russia’s political institutions and how financial markets should react (Opitz 2018). Table 5 also shows that six out of the ten tests from mid-1903 to end-1905 (widely ac-

knowledge as the “revolutionary surge” in Russia, see [Wynn \(2014\)](#)) show dependence, providing more evidence that financial markets were efficient in the face of “normal” turmoil but had difficulties coping with regime-threatening turmoil. When the end of the violence and consolidation of the monarchy came about after 1907, it can be seen that market price discovery mechanisms returned to normal functioning and were, in fact, incredibly strong during the period before the First World War (1910–1914).

An argument can be made here (in fact, should be made) that the time series for this series of tests surrounding the 1905 revolution is quite short (31 observations) and even KSS performed Monte Carlo tests at a minimum of 50 observations, noting that there is a tendency towards over-rejection of the null in small samples depending on the lag length determination procedure; as [Otero and Smith \(2017, p. 713\)](#) note, the “implied [critical values] decrease (in an absolute sense) in p when the augmentation order is fixed by the user, while they increase (in an absolute sense) in p_{max} when it is optimally determined using any data-dependent procedures [i.e., information criterion] that are being considered.”³ Ironically, despite the smaller number of observations from 1903 to 1905, the opposite actually occurs in [Table 5](#), as it is the larger number of lags under the fixed and general to specific approach which are insignificant when, according to the exigencies of the test, these should be the ones which suffer from over-rejection of the null.

In any event, given the possible problems with such a small sample surrounding the revolution, we expand the sample in two ways. First, we will widen the net around the 1905 revolution to capture more of the violence preceding and the political uncertainty following, stretching the sample from May 1902 (when multiple assassinations by Socialist Revolutionaries occurred) to December 1907, a total of 68 observations. Secondly, we will then focus on the entire period of maximum terrorism in Russia, namely from March 1881 (the assassination of the Tsar) to December 1907 (the end of Russia’s first revolution and the monarchists counter-coup against the Duma). This allows us to have 322 observations, well over half our sample of 561 months and half again as many observations as utilized by [Kapetanios and Shin \(2008\)](#) in their examination of exchange rates.⁴

Results for both the OLS and GLS de-trended unit root tests for the expanded period around the October Revolution are shown in [Table 6](#) and the results point towards confirmation of the thesis that markets were rattled by the cumulative violence. In the KSS test, there are two rejections of the null of a unit root (and the fixed lag length is tantalizingly close to the 10% significance level), while using the GLS de-trending of the KS test, we see that in three of the five criteria, inefficiencies are detected: this matches up with the results of the 1903–1905 sample, but, unlike that earlier test, significance holds across longer and shorter lag lengths. As this period excludes the financial crisis that hit Russia from 1899 to 1902 and output had already begun to grow as of 1902 ([Lychakov 2019](#)), we cannot say that it was other economic factors which generated this result, especially when one notes that Russia’s main partners (the UK and France) were also growing during this time ([Asselain 1984](#)).

Finally, looking at the total period of revolutionary violence in Russia before the First World War (shown here as from 1881 to 1907, in [Table 7](#)), the results are much stronger for financial market stress. In particular, for both the KSS and KS tests (and at lag lengths of up to 16 months), four out of the five criteria confirm the effects of this stress in financial markets, while the fifth criteria in each instance (the Schwarz information criterion) chooses a much lower lag length but still comes in just above the 10% significance threshold. While this period includes the aforementioned financial crisis, the fact that the series runs for 18 years prior to the crisis and then five years post crisis argues against this being the driving factor for dependence of returns in the markets. Indeed, the sheer length of the time period and the fact that it lines up with the period of revolutionary terror in Russia provides evidence that Russia’s financial markets faced difficulties in the face of sustained political violence. If anything, the financial crisis appears to have amplified the effects of pre-existing political violence rather than the other way around.

Table 6. Non-linear unit root test on stock index levels over the pre- and post-revolutionary period.

Kapetanios et al. (2003)				Kapetanios and Shin (2008)		
<i>May 1902–December 1907</i>						
de-trended						
Criteria	Lags	KSS stat.	<i>p</i> -Value	Lags	KS stat.	<i>p</i> -Value
FIXED	11	−2.53	0.106	11	−2.75	0.043 **
AIC	8	−2.162	0.356	10	−2.706	0.105
SIC	1	−4.386	0.001 ***	1	−4.366	0.001 ***
GTS05	1	−4.386	0.002 ***	1	−4.366	0.001 ***
GTS10	10	−2.499	0.215	10	−2.706	0.109

Note: *p*-values for tests shown under the null of a unit root and the alternative of a stationary nonlinear ESTAR model. ***, ** and * for *p*-values denote significance at the 1%, 5% and 10% levels respectively. Fixed: fixed lag length chosen by Schwert (1989) maximum. AIC = Akaike Information Criterion. SIC: Schwarz Information Criterion. GTS05 and GTS10: General to specific algorithm with significance level set at 5% or 10% respectively. See Otero and Smith (2017).

Table 7. Non-linear unit root test on stock index levels over the period of violence.

Kapetanios et al. (2003)				Kapetanios and Shin (2008)		
<i>1881–1907</i>						
de-trended						
Criteria	Lags	KSS stat.	<i>p</i> -Value	Lags	KS stat.	<i>p</i> -Value
FIXED	16	−3.283	0.006 ***	16	−2.894	0.01 ***
AIC	11	−3.409	0.008 ***	11	−3.038	0.013 **
SIC	3	−2.388	0.127	3	−2.11	0.121
GTS05	11	−3.409	0.011 **	11	−3.038	0.019 **
GTS10	11	−3.409	0.009 ***	11	−3.038	0.014 **

Note: *p*-values for tests shown under the null of a unit root and the alternative of a stationary nonlinear ESTAR model. ***, ** and * for *p*-values denote significance at the 1%, 5% and 10% levels respectively. Fixed: fixed lag length chosen by Schwert (1989) maximum. AIC = Akaike Information Criterion. SIC: Schwarz Information Criterion. GTS05 and GTS10: General to specific algorithm with significance level set at 5% or 10% respectively. See Otero and Smith (2017).

4. Conclusions

Financial markets may be on the whole weak form efficient, but even they have their limits in the face of uncertainty, especially with the informational content of an event of political violence is unknown. This paper has shown that even normally efficient markets may have periods where even the presence of new information—encapsulated in political violence—does not aid price discovery, mainly because the informational content of the event is uncertain and can have both short- and long-term ramifications. Russia in the 19th century provided an excellent test for this thesis and the use of 50 years of monthly data allowed us to observe precisely where these pockets occurred, i.e., overlapping with intense political violence. Taken individually, each of the linear unit root and variance ratio tests provided evidence for the market efficiency of Tsarist Russia but, taken in tandem with the nonlinear tests of Kapetanios et al. (2003) and Kapetanios and Shin (2008), the picture is of a weak form efficient market which, in times of considerable stress created by political volatility, became rattled and uncertain.

The extensions to this work are many. In the first instance, the approach outlined here may be utilized for other countries with perhaps more robust market data (including on market microstructure), allowing for more direct testing of market efficiency in addition to the pervasive uncertainty accompanying political violence. This may be difficult in 19th century Russia, due to the dearth of daily data, but (possibly) could be done with

more archival research. Other approaches, including event studies, might also home in on specific episodes of inefficiency, but these too would require more detailed daily data. Finally, we can also expand our lens beyond Tsarist Russia and to other countries with prolonged experiences with terrorism or political violence, such as Italy or West Germany in the 1970s or during the history of the conflict in Northern Ireland. Regardless, this research calls for more investigation into the longer-term effects of political instability on capital markets, a highly relevant topic in a post-COVID world.

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Notes

- ¹ For an excellent tour through the mathematics of these various tests, see [Hung \(2009\)](#).
- ² Lag length was chosen automatically by commonly used information criteria.
- ³ The 1890–1899 data has a time series of 120 months, closer to the [Kapetanios et al. \(2003\)](#) sample of 160 and far above the minimum of [Kapetanios and Shin \(2008\)](#) and, thus, suffers less from this issue.
- ⁴ [Kapetanios and Shin \(2008\)](#) fix their time series at T = 200 for this application.

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