Herding in Imperial Russia:

Evidence from the St. Petersburg stock exchange (1865-1914)

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Abstract

We present seminal empirical evidence on market-wide herding from historical markets drawing on a unique database for the St. Petersburg stock exchange for the 1865 – 1914 period. Our findings indicate the presence of herding in Imperial Russia's largest equity market, which tends to vary among industries and grow stronger during months of negative performance and declining volatility. Controlling for the 1893-reform that prompted wider social participation in equity trading, we find that herding surfaces exclusively in the post-reform years, with no evidence of herding arising pre-reform. Our results confirm extant narrative evidence on the presence of herd behaviour in pre-20th century markets and showcase that the behaviour of investors in historical stock exchanges exhibits patterns similar to those of modern-day ones.

JEL classification: G12; G14; G23

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I. Introduction

Herd behaviour is one of the most broadly reported trading patterns in financial markets (Chen, 2013; Choi and Skiba, 2015), with its presence often appearing relatively stronger – in terms of both magnitude and significance – among emerging and frontier markets, compared to their developed counterparts (Chang et al., 2000; Gelos and Wei, 2005). This has largely been attributed to their incomplete regulatory designs, which tend to hamper their transparency and raise issues of availability and credibility for information-disclosure (Antoniou et al. 1997; Economou et al., 2015b); in addition, such markets are characterized by the substantial participation of domestic retail investors, who are (on average) of low sophistication (Barber et al., 2014) and prone to noise trading (Li and Wang, 2010). However, it is important to acknowledge that emerging/frontier markets are not exclusively encountered during the post-1970s' evolution of the global economic and financial environment. Indeed, the early financial markets established from the 17th century onward were also typified by issues similar to those of modern emerging/frontier markets (lack of transparency; rumor mongering; manipulation; insider trading; rudimentary institutional designs) and were dominated by company-insiders and retail investors with a strong speculative disposition (Kindleberger and Aliber, 2005), suggesting that herding would be expected to be a likely feature of pre-20th century markets.

However, despite the large body of finance literature (Neal, 1982; Galbraith, 1994; Kindleberger and Aliber, 2005; Dale et al., 2005; Borodkin and Perelman 2011; Corzo et al., 2014; Bassino and Lagoarde-Segot, 2015) covering equity markets from as early as the 17th until the early 20th centuries that has produced narrative evidence of investors' herd behaviour during various phases of those markets' evolution, it is interesting to note that, no research to

date has empirically verified the presence of market-wide herding[1,2] in stock exchanges during those centuries, despite the availability of recently-compiled databases reaching as far back as the 18th century (Goetzmann et al., 2001) that have allowed research in historical capital markets to gain momentum over the past two decades.[3] Our study addresses this issue by providing seminal empirical evidence on investors' herding at the market-wide level from the St. Petersburg stock exchange drawing on month-end prices for the universe of firms listed there between January 1865 and July 1914 and tests for a series of research questions.

First, we test whether herding was significant in Imperial Russia's prime equity market, in view of the dominance of non-professional investors in that market. Second, we explore whether herding exhibits variations across industries, in light of widespread evidence on industry-effects in herding from modern equity markets.[4] Third, we examine the extent to which herding presents itself with asymmetries, by gauging whether herding varies (both for the whole market and individual industries) across different market/industry states (up/down market/industry months; increasing/decreasing market/industry volatility months).[5] Fourth, we assess the impact over herding conferred by the regulatory reforms of the early 1890s in Russia's financial

[1] The only other study we are aware of that has empirically investigated herding for pre- World war two years is that by Bohl et al. (2012); using a very small sample (19) of listed stocks in Germany for the 1920-1923 period, they found that investors herded significantly towards them during that period.

[2] Herding is not the only behavioural trading pattern for which there exists scant empirical research regarding historical markets; almost no empirical work exists for any other trading pattern of investors' behaviour for them. An exception to this is Pierdzioch (2004), who demonstrated that German investors exhibited significant feedback trading during the 1880-1913 period. Studies relying on ownership data (Acheson and Turner, 2011; Rutterford et al., 2017) have confirmed the presence of home bias in UK investors' holdings in the 19th century, yet did not research the effect of home bias over their trading decisions (something important, since home bias can foster correlation in the trades of investors within the same region; Feng and Seasholes, 2004).

[3] This has culminated in a growing body of literature devoted to the empirical testing (and, largely, confirmation) of a variety of stylized return-patterns of modern stock exchanges in market settings from earlier centuries. Examples of such patterns include autocorrelation (Annaert and Van Hyfte, 2006; Bassino and Lagoarde-Segot, 2015), non-normality (Campbell et al., 2018), beta-instability (Mensah, 2013; 2015), momentum (Annaert and Mensah, 2014; Geczy and Samonov, 2016; Goetzmann and Huang, 2018), mean reversion (Goetzmann et al., 2001; Annaert and Van Hyfte, 2006), liquidity premium (Burhop and Gelman, 2010; Moore, 2010; Gernandt et al., 2012), equity premium (Annaert et al., 2015) and asymmetric volatility (Goetzmann et al., 2001).

[4] For more on the potential reasons underlying industry-variations in herding, see Andrikopoulos et al., (2017) and the discussion in section III.

[5] Herding can be asymmetric contingent on market/industry performance and volatility due to a confluence of reasons; for a detailed discussion of those see Gavriilidis et al. (2013a) and the discussion in section III.

sector that prompted the wider participation of individual investors in equity trading, in view of evidence on the propensity of this investor-type to engage in herding (Kumar and Lee, 2006; Dorn et al., 2008; Kumar, 2009; Burghardt, 2011; Jame and Tong, 2014; Li et al., 2017) under the influence of behavioural biases (Barber et al., 2009a, 2009b; Barber and Odean, 2013).

Our results suggest that investors herded significantly in the St. Petersburg stock exchange throughout our sample period; their herding is asymmetric, appearing more frequently for months of falling market returns and decreasing market volatility. Herding is observed consistently for the Financial and Trade & Industrial industries for the full sample period and across several industry states; its presence for Railways and Steamships is confined to specific states of each industry (positive performance and low-volatility months for Railways; negative performance months for Steamships). Herding is present (absent) in the aftermath of (prior to) the 1893-reforms at the market-wide level as well as for Steamships and Trade & Industrial companies; no evidence of herding surfaces pre or post 1893 for Financials and Railways.

Our work contributes significantly to the historical finance literature, by offering empirical verification of herding at the market-wide level in a historical market for the first time in the literature; as mentioned earlier, this is important, in view of the fact that any reference to herding phenomena in $18^{th}/19^{th}$ century markets is of a narrative nature only (Neal, 1982; Galbraith, 1994; Kindleberger and Aliber, 2005; Dale et al., 2005; Borodkin and Perelman 2011; Corzo et al., 2014; Bassino and Lagoarde-Segot, 2015). From a behavioural finance perspective, our findings confirm that herd behaviour in earlier centuries' stock markets bore features (industry effects; asymmetries) similar to those encountered in modern markets, thus suggesting that investors' behaviour has changed little over time. In addition, the fact that the bulk of herding is observed for the post-1893 years confirms extant legal-theoretical evidence (Gerding, 2007; Hirshleifer, 2008), according to which, the adoption of regulatory policies

catering to the prevailing social mood can foment the emergence of herding phenomena in equity markets.

The rest of this paper is structured as follows: section II discusses herding as a concept and its key sources and empirical evidence (section II.a.), followed by an overview of the evolution of the St. Petersburg stock exchange in the 19th and early 20th centuries in the context of developments in the wider Russian economy (section II.b.); section III presents the data utilized alongside some descriptive statistics and introduces the empirical design employed to test for herding. Section IV discusses the results and section V presents a series of robustness checks. Section VI provides some concluding remarks and highlights several implications of our study.

II. Theoretical background

II.a. Herding

Investors herd when they discard their private signals or fundamentals, choosing instead to mimic the behaviour of others, following interactive observation of others' actions or action-payoffs (Hirshleifer and Teoh, 2003). Whether this behaviour is intentional or not has constituted the subject of much research, the latter having identified a series of factors that can motivate intentional or spurious herding (Bikhchandani and Sharma, 2001; Holmes et al., 2013; Gavriilidis et al., 2013a; Economou et al., 2015b; Galariotis et al., 2015).

Intentional herding is the product of an actual or perceived asymmetry in the market environment that encourages investors to copy their peers' trades in order to reduce this asymmetry. The latter may be informational, in which case investors who are less informed or possess inferior information-processing skills may mimic the trades of those they consider better-informed, in anticipation of *informational payoffs* (Devenow and Welch, 1996). In the extreme, if growing numbers of investors end up being less willing to rely on their private

signals and choose to free-ride on their peers' trades, instead, this will deplete the public pool of information and is likely to foment the emergence of informational cascades (Banerjee, 1992; Bikhchandani et al., 1992). Many a time, however, investors herd intentionally due to asymmetries of a professional nature; this is the case of low-quality investment professionals (e.g., fund managers) tracking the trades of their high-quality peers in order to attain *career/reputational payoffs* (Scharfstein and Stein, 1990; Dasgupta et al., 2011; Jiang and Verardo, 2018). Considering the relative performance evaluation to which fund managers are normally subject, less-able managers have an obvious incentive to mimic their better-able peers, in order to improve on their image (or, alternatively, conceal their low ability).

Herding, however, need not necessarily be intentional; evidence suggests it is often the result of investors' exposure to a common factor motivating correlation in their trades. This may be due to *relative homogeneity* (Teh and DeBondt, 1997), whereby similarities among investment professionals (e.g., in terms of their education/qualifications, the indicators they analyze and their processing, as well as their regulatory framework) prompt similarities in their trades. What is more, correlation in investors' trades can arise if investors' information sets are correlated (*investigative herding*; Froot et al., 1992), if they follow similar investment strategies (*style investing*; Barberis and Shleifer, 2003), or if they chase popular sectors (*fads*; Brunnermeier and Nagel, 2004). In addition, investors can exhibit correlation in their trading behaviour as a result of the impact of behavioural biases and heuristics (Barber et al., 2009a, 2009b), which motivate tacit coordination of their trades.

From an empirical perspective, herding has been confirmed internationally at both the micro and macro levels. At the micro level, there exists widespread evidence of institutional investors

engaging in such a practice across several markets, developed[6], emerging[7] and frontier[8] ones, with herding tending to appear more frequently among the latter two; evidence of stronger herding among emerging/frontier markets has also emerged from research at the macro-level.[9] Research (Gelos and Wei, 2005) has argued that this is likely due to the incomplete institutional designs of emerging/frontier markets that render their transparency lower and increase their informational ambiguity, thus prompting investors to seek informative signals in the trades of their peers. What is more, herding has further been found to present itself with size (often appearing significant among the smallest[10] or largest[11] stocks), industry[12] and asymmetric[13] effects internationally; herding has also been found to be affected by financial crises[14], while

[6] With respect to developed markets, much research hails from the US, with its findings being rather period-dependent. Earlier studies on US pension (Lakonishok et al., 1992) and mutual funds (Grinblatt et al., 1995; Wermers, 1999) covering the pre-2000 years found limited herding among US fund managers; conversely, studies including the post-2000 years (Sias, 2004; Choi and Sias, 2009; Liao et al., 2011; Celiker et al., 2015; Cui et al., 2019) have reported greater magnitudes of institutional herding. Possible explanations for this include growing indexing among fund managers (Stambaugh, 2014) and reduction in skill over time (Barras et al., 2010). As far as other developed markets are concerned, evidence in favour of institutional herding has surfaced in Germany (Kremer and Nautz, 2013; Walter and Weber, 2006), Spain (Gavriilidis et al., 2013a), Portugal (Holmes et al., 2013; Gavriilidis et al., 2013b) and the United Kingdom (Wylie, 2005; Blake et al., 2017).

[7] Evidence of institutional herding in emerging markets has been documented in Chile (Olivares, 2008), Poland (Voronkova and Bohl, 2005), South Korea (Choe et al., 1999; Kim and Wei, 2002a, 2002b) and Taiwan (Hung et al., 2010).

[8] See the study by Economou et al. (2015b) for institutional herding in Bulgaria and Montenegro.

[9] See, for example the evidence from African markets (Guney et al., 2017), the Asia-Pacific region (Chiang et al., 2013), China (Tan et al., 2008), European market samples (Economou et al., 2011; Mobarek et al., 2014), the Euronext-group (Economou et al., 2015a; Andrikopoulos et al., 2017), Poland (Goodfellow et al., 2009), Taiwan (Demirer et al., 2010) and the global evidence by Chiang and Zheng (2010).

[10] Small-capitalization stocks entail lower analyst-following and, hence, higher informational uncertainty; investors wishing to tackle the latter may choose to mimic their peers' trades, if they deem the latter's content as informative enough. For empirical evidence on institutional herding among small stocks, see Lakonishok et al. (1992), Wermers (1999), Sias (2004), Wylie (2005) and Hung et al. (2010). For evidence of herding among smaller stocks at the macro level, see Chang et al (2000) and Caparelli et al. (2004).

[11] Funds may herd towards large capitalization stocks due to regulatory reasons (the case, e.g., of pension funds facing an institutionally restricted opportunity set of stocks to invest into; see Voronkova and Bohl, 2005 and Olivares, 2008) or indexing reasons (the case of fund managers' performance being benchmarked against an index, which prompts them to mirror its composition in their portfolios and rebalance their portfolios accordingly following any changes in its composition). For more on this, see the discussion in Walter and Weber (2006) and Blake et al. (2017).

[12] Industry herding has been reported at the micro (Choi and Sias, 2009; Gavriilidis et al., 2013a; Celiker et al., 2015) and macro (Zhou and Lai, 2009; Gebka and Wohar, 2013; Andrikopoulos et al., 2021) levels; for more on the reasons motivating possible variations in industry herding see the discussion in Andrikopoulos et al. (2017).

[13] Herding (primarily at the market-wide level, but occasionally also at the micro level) has been found to vary with market performance, market volatility, market volume and market sentiment. No uniform pattern has been identified thus far as regards these asymmetries (see e.g., the discussion in Guney et al., 2017).

[14] Herding has occasionally been found to be stronger (Kim and Wei, 2002a; Chiang and Zheng, 2010; Mobarek et al., 2014; Cui et al., 2019) and on other occasions weaker (Choe et al., 1999; Hwang and Salmon, 2004) following the outbreak of financial crises.

its cross-market dynamics have also been confirmed.[15] It is also worth noting here that herding has been reported at the micro level among retail investors (Kumar and Lee, 2006; Dorn et al., 2008; Kaniel et al., 2008; Barber et al., 2009a, 2009b) as well; what is more, several studies have attempted to identify the extent to which herding is intentional or spurious, both at the micro (Holmes et al., 2013; Gavriilidis et al., 2013a; Economou et al., 2015b; Celiker et al., 2015) and macro (Galariotis et al., 2015; Cui et al., 2019) levels.

II.b. St. Petersburg stock exchange

The establishment of stock exchanges in Imperial Russia lagged behind other developed economies of the time. The St. Petersburg stock exchange was the first to be founded in the country[16], with the stock exchanges of Arkhangelsk, Odessa, Warsaw and Moscow launched much later (Borodkin et al., 2006). Prior to the 1830s, there were no regulatory provisions reigning over issues of public listing rules and transactions, with the then-extant regulations being primarily concerned with the timing of trading sessions and the role of specific professionals (brokers, notaries and auctioneers) in their process (Lizunov, 2015). These years saw very limited activity in equity trading, with the bulk of transactions involving commodities and, to a lesser extent, ship insurance, currencies, and fixed-income instruments (Borodkin and Perelman, 2011).

A factor key to the promotion of equity trading was the adoption of a corporate law in 1836, which incited several rounds of debates concerning its modernization for decades and remained in force until the 1917 Revolution. In essence, it stipulated the establishment of joint stock companies by concession (Borodkin et al. 2006; Borodkin and Perelman, 2011); according to

[15] See, for example, the study of Chiang et al. (2013) on cross-market herding in the Asia-Pacific region.
[16] No specific year is identified with its foundation, the latter being assumed to coincide with 1703 (the foundation year of St. Petersburg as a city); as Borodkin and Perelman (2011) note, the first formal reference to the St. Petersburg stock exchange in official documentation dates to 1721.

this system, the incorporation-application of each company had to be submitted for review to the Ministry of Finance and, upon approval, signed into law by the Czar, in effect leading every corporate charter to become a separate law on its own. This concessionary legal system led to the advent of corporations in Imperial Russia, with the number of their incorporations retaining its upward trend in the following decades (with the exception of the 1880s)[17], more so in the aftermath of the Crimean War[18] (which saw the evolution of several industries - financial; light industries[19]; transportation - in the country).

To the extent that those newly incorporated companies vied for capital financing opportunities, a lot of them chose to list on the St. Petersburg stock exchange, leading to a sharp rise in public listings – and the exchange's first major bubble in 1857-1858 (motivated by the trades of members of the state bureaucracy and the military; Owen, 2013). As the uptrend in the number of listings on the stock market continued unabated, the stock exchange witnessed new surges in speculation in the 1868-1869 and 1871-1873 periods; although forward and futures trading on shares was proscribed since December 1836 ("Rules on Share-Issuing Companies"), its unofficial practice was reported to be commonplace and this prompted discussions among officials (both in the Ministry of Finance and the St. Petersburg stock exchange) in September 1869 as per the treatment of this speculative fervour (Lizunov, 2015).

The 1890s witnessed the economic revival of Russia as well as an acceleration of its industrialization process, largely supported by an influx of European investment capital (Owen, 2013). This economic/industrial boom led to an exponential growth in new companies' incorporations (Borodkin and Perelman, 2011) and listings on the St. Petersburg stock

[17] The April 1877 – March 1878 Russo-Turkish war prompted a rise in the government's budget deficit and the devaluation of the rouble, and was followed by a period of economic stagnation that lasted throughout the 1880s (Owen, 2013).
[18] The Crimean War (1853-1856) led to the proliferation of railroads, steamships, factories and banks across Russia (Owen, 2013). For more on the evolution of companies' incorporations in the 19th and early 20th centuries in Imperial Russia, see Borodkin and Perelman (2011).
[19] These industries revolved mainly around textiles and beet sugar; see Owen (2013).

exchange, where a phenomenal price-rally kickstarted by late 1893. This rally was fuelled by a confluence of factors, including the decline in government bond yields from 5% to 4% (which prompted investors to enter the stock market in search of higher returns), the adoption of the gold standard in 1895-1897 (which endowed foreign investors with enhanced confidence in Russian business, as it shielded them from the highly volatile rouble) and the extended line of credit supplied by banks to their customers enabling them to purchase shares ("on call" funds; see Borodkin and Perelman, 2011 for a more detailed presentation of this tool).[20]

However, research (Goetzmann and Huang, 2018) suggests that key to the commencement of the rally in late 1893 was the ratification of two laws on July 8th, 1893 ("On the Prohibition of Certain Transactions in the Buying and Selling of Gold Currency, Bills of Exchange, and Suchlike Items of Value Priced in Gold Currency"; "On Certain Changes in the Resolutions Concerning the Stock Exchanges"), which, among other issues (see Lizunov, 2015) allowed futures trading in equities. Although futures trading constituted unofficial practice till that point, its legalization prompted investors from a broader social cross section[21] to enter equity trading, thus culminating in a surge of speculative activity from the Fall of 1893 onward and a concomitant rise in liquidity (Goetzmann and Huang, 2018). The latter was observed more strongly among smaller capitalization stocks and allowed investors to witness a rise in their wealth, something tacitly confirmed via the significant momentum profits reported in Goetzmann and Huang (2018) for the St. Petersburg stock exchange post-1893. This speculation led to wild price-fluctuations in the latter half of the 1890s and gripped investors in Russia for the most part of that decade, motivating the attention of authorities, who were concerned by its destabilizing potential.

[20] During this period, St. Petersburg banks engaged in extensive investment banking activities, with much of their revenue hailing from securities' dealings (Borodkin and Perelman, 2011).
[21] Prior to the 1890s, equity trading was largely confined among members of the upper social classes and corporate insiders (Borodkin et al., 2006; Goetzmann and Huang, 2018).

In that respect, Temporary Rules for the Securities Department of the St. Petersburg Stock Exchange were issued in January 1900 to combat speculation, while June 27th, 1900 saw the ratification by the Czar of the "Order on the Formation of a Securities Department at the St. Petersburg Stock Exchange", supplemented by a law "On the Responsibility of Individuals Introducing Securities into Circulation on the St. Petersburg Stock Exchange" (June 12th, 1902) and "Rules on the Listing of Securities in the Securities Department" approved by the Ministry of Finance on September 5th, 1902 (Lizunov, 2015). This set of legislations led to the separation of equities from commodities trading on the St. Petersburg stock exchange, with equities trading now coming under the oversight of a special department of the Ministry of Finance (Borodkin and Perelman, 2011). The presence of speculation, however, did not abate in the 1900s; although the Russo-Japanese war (1904-1905) and the 1905 Revolution led to the flight of capital from the country, Russian equities documented rather strong performance between 1902 and 1905 (Borodkin et al., 2006). A temporary slump in November 1905 was followed by a price rebound in early 1906, only to be followed by a longer down-market period that extended well into 1909; the final surge in stock prices prior to the First World war was reported from 1910 onward, amid a window of rapid economic growth (Borodkin, 2006; Owen, 2013).

III. Data and Methodology

Our dataset was sourced from the website of the International Center for Finance at the Yale School of Management and comprises end-of-month closing prices of 543 firms listed in the St. Petersburg stock exchange between January 1865 and July 1914.[22] To empirically assess the presence of herding, we rely on the approach proposed by Chang et al. (2000), which infers herding via the relationship between the cross-sectional dispersion of equity returns and the

[22] For more information on the compilation of the database, please refer to Goetzmann and Huang (2018).

absolute performance of the market. If securities' pricing is rational, the relationship between the cross-sectional dispersion of returns and absolute market performance would be expected to be linear and positive; therefore, the cross-sectional return-dispersion would rise with absolute market returns, as securities' sensitivity to market movements is not uniform (Black, 1972). In the presence of herding, however, one would expect securities' returns to track the market's performance and exhibit clustering around the average market return. This would culminate in a decline for the cross-sectional return-dispersion and, assuming this herding to motivate extreme absolute market returns, the relationship between the cross-sectional dispersion of returns and absolute market performance would turn concave. Chang et al. (2000) tested empirically for these possibilities drawing on the following specification:

$$CSAD_{m,t} = \beta_0 + \beta_1 \left|R_{m,t}\right| + \beta_2 R_{m,t}^2 + e_t \quad (1)$$

In the specific context of our study, $R_{m,t}$ reflects the average performance of all actively traded stocks in the St. Petersburg stock exchange in month *t*; $CSAD_{m,t}$ is calculated as:

$$CSAD_{m,t} = \frac{\sum_{i=1}^{n} \left|R_{i,t} - R_{m,t}\right|}{n} \quad (2)$$

Here, *n* is the number of actively traded stocks in month *t* and $R_{i,t}$ the log-differenced return of stock *i* in month *t*. Assuming rationality in asset pricing, we would therefore (as mentioned above) expect $CSAD_{m,t}$ and $\left|R_{m,t}\right|$ to be linearly and positively related, with the latter implying significantly positive (insignificant) values of β_1 (β_2). In the presence of herding, the relationship between $CSAD_{m,t}$ and $\left|R_{m,t}\right|$ would become concave (i.e. non-linear), the latter implying significantly negative values for β_2.

To assess whether herding varies between up and down markets, we utilize the following specification:

$$CSAD_{m,t} =$$

$$\beta_0 + \beta_1 D^{UP} \left|R_{m,t}\right| + \beta_2 (1 - D^{UP}) \left|R_{m,t}\right| + \beta_3 D^{UP} R_{m,t}^2 + \beta_4 (1 - D^{UP}) R_{m,t}^2 + e_t \quad (3)$$

Here, D^{UP} = 1, if $R_{m,t}$ is positive, zero otherwise; in this case, significantly negative values for β_3 (β_4) would denote the existence of herding during months of positive (negative) average market performance.[23]

To gauge whether herding varies between months of increasing and decreasing market volatility[24], we employ the following specification:

$$CSAD_{m,t} = \beta_0 + \beta_1 D^{IV}\left|R_{m,t}\right| + \beta_2(1 - D^{IV})\left|R_{m,t}\right| + \beta_3 D^{IV} R_{m,t}^2 + \beta_4(1 - D^{IV})R_{m,t}^2 + e_t \quad (4)$$

Here, D^{IV} = 1 for months of increasing volatility, zero otherwise. We calculate volatility using the squared value of $R_{m,t}$; similar to Equation (3), significantly negative values for β_3 (β_4) would denote the existence of herding during months when volatility has increased (decreased) versus the immediately previous month.

To examine whether the regulatory reforms of 1893 conferred an effect over the presence of herding, we rely on the following specification:

$$CSAD_{m,t} = \beta_0 + \beta_1 D^{1893}\left|R_{m,t}\right| + \beta_2(1 - D^{1893})\left|R_{m,t}\right| + \beta_3 D^{1893} R_{m,t}^2 + \beta_4(1 - D^{1893})R_{m,t}^2 + e_t \quad (5)$$

[23] Factors that can render herding stronger during bullish markets include noise trading (unsophisticated investors tend to be attracted to market rallies – see e.g. Grinblatt and Keloharju, 2001 and Lamont and Thaler, 2003), positive mood (it reduces the perception of riskiness, prompting investors to employ heuristics – such as, e.g. mimicking others - when processing risky decisions; Gavriilidis et al., 2020), optimistic sentiment (it motivates investors to jump on its bandwagon or, alternatively, prey on it; see e.g. Liao et al., 2011, Economou et al., 2015a and Economou et al., 2015b), external habit formation (the profits enjoyed by their peers during bullish markets can motivate investors to herd with them in order to avoid missing out – see e.g. Guney et al., 2017) and overconfidence (if investors realize profits during bullish markets, they may attribute them to their skills and, consequently, trade more aggressively in tandem; see e.g. Barber et al., 2007). On the other hand, herding can grow stronger during bearish markets due to risk aversion (the case of investors sell-herding with their peers during market slumps in order to curtail their losses) and reputational reasons ("bad" fund managers may mimic the trades of their "good" peers during market slumps, in order to demonstrate that any losses incurred are not due to their investment choices – as these would appear similar to those of their "good" peers – but rather the result of the market's adverse movements; Scharfstein and Stein, 1990).

[24] Rising volatility periods can motivate herding regardless of whether this volatility is the product of noise (noise traders would be likely to herd; see e.g. Barber and Odean, 2013) or a higher information flow (if the informational environment grows too complex, investors may choose to herd with their peers to tackle this complexity). On the other hand, declining volatility periods render it easier for uninformed investors to track – and, potentially mimic – their informed peers' trades (Holmes et al., 2013), while also making it easier for investors to decipher the market's direction – and, again potentially, herd on it.

where D^{1893} = 1 for the period after July 1893, zero before that. Again here, significantly negative values for β_3 (β_4) would denote the existence of herding in the aftermath (prior to) the 1893 regulatory reform.

To explore whether herding varies across different industries[25], we classify our sample's stocks into four industries, namely Financials, Railways, Steamships and Trade & Industrials and repeat all of the above estimations for each industry separately.[26]

Table 1 presents a series of descriptive statistics pertaining to the cross-sectional absolute dispersion of returns ($CSAD_{m,t}$) and average return ($R_{m,t}$) of the St. Petersburg stock exchange as a whole and each of the four industries separately. As the figures presented there indicate, the average performance of the total market and all four industries is positive for the whole sample period, with a similar picture emerging from the median values. Financials is the least risky industry, bearing the lowest standard deviation of the four, with the highest value of this indicator observed for Steamships (the industry with the highest mean return). All $R_{m,t}$-series exhibit departures from normality, considering the significant values of their skewness (always negative in value, with the exception of Steamships) and kurtosis (whose magnitude clearly reflects leptokurtosis) measures, with a similar picture emerging for the $CSAD_{m,t}$-series as well.

IV. Results-Discussion

We begin the presentation of our empirical findings with the results from the estimation of Equation (1) for the full sample period, both for the total market and for all four industries, as

[25] Industry-variations in herding may be the result of reputational reasons, risk aversion, sector indexing, fads and style rotation; for a detailed discussion of those factors, see Andrikopoulos et al. (2017).

[26] In this case, $R_{m,t}$ would correspond to the industry's average performance and its squared value would now signify industry volatility in Equation (4).

depicted in Table 2. All β_1-estimates are significantly[27] positive, thus confirming the linearly positive relationship between $CSAD_{m,t}$ and $R_{m,t}$ stipulated by rational asset pricing models. However, as the absolute performance of the market and each industry rises in magnitude, it appears that this relationship changes in structure, becoming significantly negative and nonlinear for the total market, Financials and Trade & Industrials, as indicated by the significantly negative β_2-values for those estimations. This suggests the presence of herding for the St. Petersburg stock exchange as a whole, as well as for those two industries; conversely, no herding is detected for Railways and Steamships, where β_2 assumes significantly positive values.[28] These results denote that herding was present among investors in Imperial Russia's largest equity market, something perhaps unsurprising, given the dominance of its trading dynamics by non-professional investors prone to speculative trading, as delineated in section II.b earlier. This is interesting, more so considering the widespread evidence (Kumar and Lee, 2006; Dorn et al., 2008; Kumar, 2009; Burghardt, 2011; Jame and Tong, 2014; Li et al., 2017) on the tendency of individual investors to herd in their trades, largely motivated by behavioural biases (Barber et al., 2009a, 2009b; Barber and Odean, 2013), as it suggests that the trading behaviour of this investor-type has changed little over the centuries. In addition, the variations in herding significance across industries are in line with evidence on industry-effects in herding from modern equity markets (see e.g. Andrikopoulos et al., 2017).

Table 3 presents the estimates from Equation (3), from which we can gauge a rather interesting concentration of herding during months of negative performance; indeed, significantly negative β_4-values surface for the total market and three of the four industries (except

[27] For the purposes of this study, statistical significance is established at the 10% level, i.e. for p-values less than 0.1.

[28] The significantly positive β_2-values for these two industries indicate the presence of "counter herding", whereby investors strongly deviate from the market's consensus as far as these industries are concerned. Although it is impossible to assert the reasons underlying the lack of herding for Railways and Steamships, one may argue that their later appearance in Russian economic life (both as innovations and industries) may have led them to appear as less established (compared to Financials and Trade & Industrials) in the perception of investors, who may have viewed their prospects as less clear to herd on.

Railways). We also report significant herding during months of positive performance (reflected through significantly negative β_3-values) for the total market and Railways. The statistically significant difference between β_3 and β_4 for all estimations suggests that herding is strongly asymmetric in the St. Petersburg stock exchange when conditioned on market/industry performance, in line with a multitude of evidence from modern equity markets.[29] The more frequent presence of herding during market/industry slumps may be due to risk aversion prompting investors to herd with their peers on the sell-side, possibly due to panic or to avoid incurring larger losses in case of prolonged slumps.[30] Although this is reflected in three industries' herding estimates, herding at the total market level appears much stronger during up- compared to down-market months (β_3 is substantially larger in absolute terms than β_4), thus confirming literature evidence (Gavriilidis et al., 2013a) on market and industry herding dynamics within the same market not necessarily sharing similar patterns.

Table 4 presents the results from herding estimations conditional on increasing/decreasing monthly volatility (Equation 4); herding at the total market level is present for months of both rising and falling volatility, more strongly so for the latter (β_4 is around nine times larger in absolute terms than β_3), thus suggesting a rather strong tendency on behalf of Russian investors towards herding on months whose volatility has declined month-on-month. This is further confirmed from the industry results, with Financials and Trade & Industrials mirroring the total market results and Railways exhibiting herding on decreasing volatility months only (no herding is documented for Steamships for either volatility-state).[31] With the difference between β_3 and β_4 being statistically significant for the total market, Railways and Trade & Industrials,

[29] See e.g. Chang et al. (2000), Gavriilidis et al. (2013a), Economou et al. (2015a), Economou et al. (2015b) and Guney et al. (2017).
[30] Such a convergence to the market's consensus is less observed on the up-market side, whereby β_3 coefficients turn positive for Financials, Steamships and Trade-& Industrials, an indication of counter herding.
[31] β_3 is positive for Railways and Steamships, an indication of counter herding during increasing volatility months; the negative $\beta_4$coefficient for Steamships is statistically insignificant.

this indicates that herding exhibits asymmetries when conditioned on volatility.[32] The stronger presence of herding for months of decreasing volatility may be due to lower volatility rendering it easier for uninformed investors to track the trades of their informed peers (Holmes et al., 2013)[33]; alternatively, lower volatility may have furnished investors with a clearer view of the overall direction of prices, thus allowing them to herd on that direction with greater ease.

When testing for the effect of the 1893-reforms over herding in the St. Petersburg stock exchange, it becomes obvious from the estimates presented in Table 5 that herding in that market surfaces only for the period after July 1893; indeed, this is the case for the total market and two industries (Steamships; Trade & Industrials), with the difference between β_3 and β_4 being statistically significant in all three cases.[34] The appearance of herding exclusively in the post-reform years is in accordance with extensive evidence (Borodkin and Perelman, 2011; Owen, 2013; Lizunov, 2015; Goetzmann and Huang, 2018) on the role of these reforms in fomenting speculation in the market by encouraging the participation of investors from a wide social cross section in equity trading (which, until then, was mainly in the hands of members of the upper social classes and corporate insiders). The fact that herding rises in the aftermath of a reform that helped increase the participation of individual investors in the stock market confirms evidence from modern markets (Kumar and Lee, 2006; Dorn et al., 2008; Barber et al., 2009a, 2009b; Kumar, 2009; Burghardt, 2011; Barber and Odean, 2013; Jame and Tong, 2014; Li et al., 2017) on the propensity of retail traders to herd in their equity investments. With individual investors being the key candidates for noise trading (Barber et al., 2009a), the rise in liquidity experienced by the market following those reforms (Borodkin et al., 2006;

[32] Similar to earlier research; see e.g. Gavriilidis et al. (2013a), Economou et al. (2015a), Economou et al. (2015b) and Guney et al. (2017).
[33] Given the absence of institutional investors (key candidates for informed traders in modern financial markets) from the 19th-century St. Petersburg stock exchange, that would likely involve individual investors tracking the trades of corporate insiders.
[34] β_4 is overwhelmingly positive, a reflection of counter herding during the pre-reform years.

Goetzmann and Huang, 2018) is in line with the established (Black, 1986) positive relationship between volume and noise trading. What is more, to the extent that this reform catered to the growing speculative appetite in social mood at the time, our results are in line with evidence from research on financial regulation (Gerding, 2007; Hirshleifer, 2008) illustrating how mood-friendly regulatory approaches can end up fostering herding phenomena in equity markets.

V. Additional tests

The Chang et al. (2000) herding model grew out of the seminal market herding model proposed by Christie and Huang (1995), which confined its focus to the behaviour of the cross-sectional dispersion of returns during periods of extreme market returns (identified with returns lying in the extreme tails of the return-distribution). More specifically, the cross-sectional dispersion of returns was proxied in their model via the cross-sectional standard deviation of returns, calculated as:

$$CSSD_t = \sqrt{\frac{\sum_{i=1}^{n}(r_{i,t} - r_{m,t})^2}{n-1}} \quad (6)$$

All variables of Equation (6) are defined same as in Equation (2). Christie and Huang (1995) then tested for herding via the following specification:

$$CSSD_{m,t} = \alpha_0 + \alpha_1 D^{DOWN} + \alpha_2 D^{UP} + e_t \quad (7)$$

Where D^{DOWN} (D^{UP}) is a dummy variable equal to unity, if the market's return belongs to the extreme lower (upper) tail of the distribution of market returns (zero otherwise). Similar to what we mentioned earlier regarding the Chang et al. (2000) model, rational asset pricing (Black, 1972) would predict a positive relationship between the cross-sectional dispersion of returns and absolute market returns (given stock's varying sensitivities to market movements);

as a result, the higher the absolute magnitude of market returns, the higher the value of the cross-sectional return dispersion. If this is the case, then the coefficients of the two dummies in Equation (7) would be expected to be significantly positive. However, this need not always be the case; periods of high absolute market returns may well entail market stress and this may prompt investors to sideline their private signals and herd with their peers; if so, stock returns would end up clustering around the average market return, rendering the cross-sectional return dispersion lower in value. Under these circumstances, we would expect the coefficients of the two dummies in Equation (7) to assume significantly negative values.

Drawing on the Christie and Huang (1995) model, we test for the presence of herding at the 1% and 5% tails of the distribution of the average market return ($R_{m,t}$) of all listed stocks of the St. Petersburg stock exchange during the 1865-1914 window. Our tests are conducted for the total market and each of the four industries and involve the full sample window, as well as the pre- and post-1893 reform sub-periods.[35] Results are presented in Tables 6 and 7, from where we readily observe that neither α_1 nor α_2 are significantly negative for any of the estimations performed, thus negating the possibility of herding. Of course, one should bear in mind that the Christie and Huang (1995) model, courtesy of its linear structure, cannot capture non-linear dynamics (which have been often found to be associated with herding)[36], thus

[35] Due to the small number of observations (595 monthly observations), we have not tested for asymmetric herding vis-à-vis market performance and market volatility (as this would allow for very few observations on either of the extreme tails of the market return distribution). Specifically conditioning herding on market performance would also be clearly inappropriate in the specific context of the Christie and Huang (1995) model, since the latter assesses herding during extreme positive and extreme negative market returns in the same specification (it would make no sense, for example, to test for herding in the extreme positive and negative tails of the market return distribution for months of positive market performance – since these months would entail no negative values).

[36] See e.g., the references in Guney et al. (2017).

confirming the advantageousness of the Chang et al. (2000) model in empirical herding estimations.[37] [38] [39]

VI. Concluding remarks

Although herding phenomena have been widely narrated in the historical finance literature in the context of several episodes before the 20th century in a variety of capital markets, no research to date has empirically investigated the presence of market-wide herding in historical stock exchanges, despite their similarities (rudimentary regulation; dominant presence of retail speculators) with modern-day emerging/frontier markets (for which herding is frequently detected). Our study fills this gap by offering seminal empirical evidence on market-wide herding from the St. Petersburg stock exchange drawing on monthly prices of all stocks listed on that market between January 1865 and July 1914. Results suggest that investors in Imperial Russia's largest equity market herded significantly, with their herding appearing more frequently during months of negative performance and declining volatility and varying among industries. Controlling for the 1893-reform that prompted wider social participation in equity trading, we find that the significance of herding surfaces exclusively in the post-reform years, with no evidence of herding arising pre-reform. To the extent that the St. Petersburg stock exchange was dominated during our sample period by non-professional investors engaged in

[37] Hwang and Salmon (2004) proposed an alternative market herding model based on extracting herding via the cross-section of monthly firm-betas. The reason we cannot employ this model as a robustness check here hinges on the fact that our database does not contain high frequency (e.g., daily) data, from which to estimate monthly betas. The lack of data on a proper market index and a risk-free rate further deters us from utilizing this empirical design.

[38] Several herding studies (Galariotis et al., 2015; Cui et al., 2019; Andrikopoulos et al., 2021) have identified whether market herding is intentional or not using the Chang et al. (2000) model employed in this paper. The method basically involves partitioning $CSAD_{m,t}$ into its fundamental and non-fundamental components, using each separately as the dependent variable for herding estimations. To the extent that this partitioning involves the employment of common risk factors (e.g., Fama-French five factors), this renders the examination of intentional v. spurious herding not feasible in the context of this study, in view of the complete absence of data on common risk factors for the St. Petersburg stock exchange during our sample period.

[39] Aside from not capturing non-linear dynamics, an additional issue identified with the Christie and Huang (1995) framework pertains to the susceptibility of CSSD to the presence of outliers (Economou et al., 2011).

speculation, our results are in line with evidence from modern financial markets both on individual investors being prone to herding and (in view of the post-reform results) on the role of regulation in fostering herding phenomena when catering to social mood.

The evidence presented in this study bears important implications for researchers, both those from the historical finance research stream and those from the behavioural finance one. With regards to the former, our findings showcase that their research area's scope would benefit from expanding to cover issues of behavioural trading patterns in historical markets, since empirically testing for such patterns would help assess the validity of the extant narrative evidence on investors' behaviour from past centuries and provide novel insight into the motives of such behaviour. Such research would be feasible, more so considering both the increased availability of databases pertaining to historical stock exchanges and the availability of empirical designs from the study of those patterns in modern financial markets. As far as researchers from behavioural finance are concerned, the results outlined in this paper denote that empirically exploring aspects of investors' behaviour in historical markets can endow us with novel insight as to how behavioural trading unfolded in markets characterized by rudimentary institutional frameworks and how the evolution of the latter affected those trading patterns (as our post-1893 reform findings so amply demonstrated). This last part is also of key relevance to regulatory authorities, which could consider drawing on such empirical evidence from past centuries to assess the possible behavioural implications of their policies, more so in market settings of nascent institutional designs.[40]

[40] An example here would be frontier stock exchanges, whose regulatory frameworks are still at an evolutionary stage of development (Guney et al., 2017), similar to pre-20th century markets.

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Table 1: Summary statistics

	All stocks (N = 543)		Financials (N = 174)		Railways (N = 66)		Steamships (N = 32)		Trade & Industrials (N = 271)	
	$R_{m,t}$	$CSAD_{m,t}$	$R_{m,t}$	$CSAD_{m,t}$	$R_{m,t}$	$CSAD_{m,t}$	$R_{m,t}$	$CSAD_{m,t}$	$R_{m,t}$	$CSAD_{m,t}$
Mean	0.0028	0.0322	0.0033	0.0258	0.0020	0.0278	0.0041	0.0377	0.0023	0.0386
Median	0.0016	0.0288	0.0019	0.0213	0.0026	0.0216	0.0005	0.0304	0.0011	0.0349
St. deviation	0.0269	0.0177	0.0279	0.0204	0.0370	0.0315	0.0450	0.0383	0.0397	0.0236
Skewness	-2.1201	5.0084	-0.5968	4.7727	-1.3565	7.4384	2.2952	8.2589	-1.2431	1.5615
Kurtosis	22.6061	46.2989	18.8698	32.8194	10.9375	71.5534	26.6004	114.4699	13.1220	4.5641
Maximum	0.1028	0.2363	0.1631	0.2133	0.1548	0.3837	0.4813	0.6252	0.1659	0.1869
Minimum	-0.2824	0.0092	-0.2672	0.0014	-0.2541	0.0024	-0.2192	0.0011	-0.3558	0.0017

The table presents descriptive statistics (mean; median; standard deviation; skewness; kurtosis; maximum; minimum) for the $R_{m,t}$ and $CSAD_{m,t}$ variables for stocks listed on the St. Petersburg stock exchange (both for the universe of stocks and for each of the four industries of their classification) between January 1865 and July 1914.

Table 2: Herding (unconditional estimations)

	β_0	β_1	β_2	R^2
All stocks	0.0208 (<.0.001)	0.6751 (<.0.001)	-0.9383 (0.0003)	0.4062
Financials	0.0147 (<.0001)	0.6485 (<.0001)	-0.9107 (<.0001)	0.3156
Railways	0.0170 (<.0001)	0.2888 (<.0001)	2.9658 (<.0001)	0.4868
Steamships	0.0242 (<.0001)	0.3512 (<.0001)	1.7192 (<.0001)	0.5917
Trade & Industrials	0.0221 (<.0001)	0.6806 (<.0001)	-1.0180 (<.0001)	0.4400

The table presents estimates from the following equation: $CSAD_{m,t} = \beta_0 + \beta_1|R_{m,t}| + \beta_2 R_{m,t}^2 + e_t$
The equation is estimated for the full sample (January 1865 – July 1914) window for: all stocks listed on the St. Petersburg stock exchange; Financials; Railways; Steamships; and Trade & Industrials. P-values are estimated based on heteroscedasticity-autocorrelation corrected standard errors and are included in parentheses. $CSAD_{m,t}$ ($R_{m,t}$) is the monthly cross-sectional absolute deviation of returns (average return) for the total market and each industry separately.

Table 3: Herding conditional on monthly performance

	β_0	β_1	β_2	β_3	β_4	F-test (H_0: $\beta_3 = \beta_4$)	R^2
All stocks	0.0194 (<.0001)	0.8366 (<.0001)	0.8708 (<.0001)	-5.3052 (<.0001)	-1.5643 (<.0001)	(0.0040)	0.4363
Financials	0.0159 (<.0001)	0.3678 (<.0001)	0.7289 (<.0001)	2.2079 (0.0054)	-1.5340 (0.0001)	(<.0001)	0.3422
Railways	0.0137 (<.0001)	0.6289 (<.0001)	0.5779 (<.0001)	-2.6758 (0.0166)	2.13391 (<.0001)	(<.0001)	05354
Steamships	0.0214 (<.0001)	0.3793 (<.0001)	0.7434 (<.0001)	1.7543 (<.0001)	-1.9617 (0.0078)	(<.0001)	0.6126
Trade & Industrials	0.0239 (<.0001)	0.4123 (<.0001)	0.6263 (<.0001)	2.4256 (0.0041)	-0.9844 (<.0001)	(<.0001)	0.4589

The table presents estimates from the following equation:

$$CSAD_{m,t} = \beta_0 + \beta_1 D^{UP} |R_{m,t}| + \beta_2 (1 - D^{UP}) |R_{m,t}| + \beta_3 D^{UP} R_{m,t}^2 + \beta_4 (1 - D^{UP}) R_{m,t}^2 + e_t$$

The equation is estimated for the full sample (January 1865 – July 1914) window for: all stocks listed on the St. Petersburg stock exchange; Financials; Railways; Steamships; and Trade & Industrials. P-values are estimated based on heteroscedasticity-autocorrelation corrected standard errors and are included in parentheses. $CSAD_{m,t}$ ($R_{m,t}$) is the monthly cross-sectional absolute deviation of returns (average return) for the total market and each industry separately. The significance of the difference between β_3 and β_4 is tested via F-tests. D^{UP} = 1 if $R_{m,t} > 0$, zero otherwise.

Table 4: Herding conditional on monthly volatility

	β_0	β_1	β_2	β_3	β_4	F-test (H_0: $\beta_3 = \beta_4$)	R^2
All stocks	0.0196 (<.0001)	0.7029 (<.0001)	1.0239 (<.0001)	-1.0121 (<.0001)	-9.1972 (<.0001)	(0.0129)	0.4127
Financials	0.0142 (<.0001)	0.6875 (<.0001)	0.7858 (<.0001)	-1.0588 (0.0036)	-6.2415 (0.0656)	(0.1187)	0.3209
Railways	0.0139 (<.0001)	0.4155 (<.0001)	0.8879 (<.0001)	2.3334 (<.0001)	-7.0544 (0.0018)	(<.0001)	0.4840
Steamships	0.0227 (<.0001)	0.3737 (<.0001)	0.6151 (0.0001)	1.6862 (<.0001)	-1.8402 (0.3390)	(0.0634)	0.5946
Trade & Industrials	0.0207 (<.0001)	0.6986 (<.0001)	0.9605 (<.0001)	-1.0409 (<.0001)	-5.1368 (0.0067)	(0.0280)	0.4455

The table presents estimates from the following equation:

$$CSAD_{m,t} = \beta_0 + \beta_1 D^{IV} |R_{m,t}| + \beta_2 (1 - D^{IV}) |R_{m,t}| + \beta_3 D^{IV} R_{m,t}^2 + \beta_4 (1 - D^{IV}) R_{m,t}^2 + e_t$$

The equation is estimated for the full sample (January 1865 – July 1914) window for: all stocks listed on the St. Petersburg stock exchange; Financials; Railways; Steamships; and Trade & Industrials. P-values are estimated based on heteroscedasticity-autocorrelation corrected standard errors and are included in parentheses. $CSAD_{m,t}$ ($R_{m,t}$) is the monthly cross-sectional absolute deviation of returns (average return) for the total market and each industry separately. The significance of the difference between β_3 and β_4 is tested via F-tests. D^{IV} = 1 if volatility in month *t* is higher than that of the immediately preceding month, zero otherwise.

Table 5: Herding conditional on the regulatory reform of July 1893

	β_0	β_1	β_2	β_3	β_4	F-test (H_0: $\beta_3 = \beta_4$)	R^2
All stocks	0.0247 (<.0001)	0.4541 (<.0001)	0.0589 (0.4113)	-0.5909 (0.0105)	10.7245 (<.0001)	0.004	0.5653
Financials	0.0162 (<.0001)	0.4042 (<.0001)	0.6031 (<.0001)	-0.4280 (0.2467)	1.1523 (0.1519)	0.0511	0.3669
Railways	0.0197 (<.0001)	0.2273 (0.0002)	-0.0908 (0.3031)	1.6957 (<.0001)	9.5574 (<.0001)	<.0001	0.6576
Steamships	0.0200 (<.0001)	0.9210 (<.0001)	0.4350 (<.0001)	-3.7714 (<.0001)	1.7154 (<.0001)	<.0001	0.6461
Trade & Industrials	0.0249 (<.0001)	0.6511 (<.0001)	0.2133 (0.0112)	-1.1003 (<.0001)	4.5829 (<.0001)	<.0001	0.4833

The table presents estimates from the following equation:
$CSAD_{m,t} = \beta_0 + \beta_1 D^{1893}|R_{m,t}| + \beta_2(1 - D^{1893})|R_{m,t}| + \beta_3 D^{1893} R_{m,t}^2 + \beta_4(1 - D^{1893})R_{m,t}^2 + e_t$

The equation is estimated for the full sample (January 1865 – July 1914) window for: all stocks listed on the St. Petersburg stock exchange; Financials; Railways; Steamships; and Trade & Industrials. P-values are estimated based on heteroscedasticity-autocorrelation corrected standard errors and are included in parentheses. $CSAD_{m,t}$ ($R_{m,t}$) is the monthly cross-sectional absolute deviation of returns (average return) for the total market and each industry separately. The significance of the difference between β_3 and β_4 is tested via F-tests. D^{1893} = 1 after July 1893, zero otherwise.

Table 6: Herding (estimated via Christie and Huang, 1995)

	Criterion for extreme = 1%				Criterion for extreme = 5%			
	α_0	α_1	α_2	R^2	α_0	α_1	α_2	R^2
All stocks	0.0034 (<.0001)	0.06928 (<.0001)	0.0007 (0.8946)	0.3028	0.0029 (<.0001)	0.0176 (<.0001)	0.0055 (0.0187)	0.0990
Financials	0.0022 (<.0001)	0.0221 (<.0001)	0.0278 (<.0001)	0.1515	0.0017 (<.0001)	0.0111 (<.0001)	0.0091 (<.0001)	0.1092
Railways	0.0017 (0.0017)	0.1892 (<.0001)	0.0029 (0.5739)	0.7150	0.0015 (0.1230)	0.0425 (<.0001)	0.0027 (0.5181)	0.1607
Steamships	0.0037 (0.0032)	0.0357 (0.0043)	0.1320 (<.0001)	0.1956	0.0032 (0.0250)	0.0122 (0.0484)	0.0318 (<.0001)	0.0563
Trade & Industrials	0.0044 (<.0001)	0.0065 (0.0175)	0.0211 (<.0001)	0.1081	0.0039 (<.0001)	0.0064 (<.0001)	0.0103 (<.0001)	0.1345

The table presents estimates from the following equation: $CSSD_{m,t} = \alpha_0 + \alpha_1 D^{DOWN} + \alpha_2 D^{UP} + e_t$
The equation is estimated for the full sample (January 1865 – July 1914) window for: all stocks listed on the St. Petersburg stock exchange; Financials; Railways; Steamships; and Trade & Industrials. P-values are estimated based on heteroscedasticity-autocorrelation corrected standard errors and are included in parentheses. $CSSD_{m,t}$ ($R_{m,t}$) is the monthly cross-sectional standard deviation of returns (average return) for the total market and each industry separately.

Table 7: Herding (estimated via Christie and Huang, 1995) Pre and Post July 1893

Panel A: Pre-Reform

	Criterion for extreme = 1%				Criterion for extreme = 5%			
	α_0	α_1	α_2	R^2	α_0	α_1	α_2	R^2
All stocks	0.0031 (<.0001)	0.1255 (<.0001)	0.0003 (0.9815)	0.5153	0.0025 (0.0019)	0.0499 (<.0001)	0.0117 (0.0038)	0.2541
Financials	0.0025 (<.0001)	0.0907 (<.0001)	0.0333 (<.0001)	0.2972	0.0017 (0.0102)	0.0172 (<.0001)	0.01285 (<.0001)	0.1540
Railways	0.0013 (<.0001)	0.2828 (<.0001)	0.0063 (0.0930)	0.9819	0.0012 (0.3554)	0.0973 (<.0001)	0.0035 (0.7335)	0.3417
Steamships	0.0029 (<.0001)	0.0177 (<.0001)	0.65715 (<.0001)	0.9748	0.0024 (0.2445)	0.0093 (0.4181)	0.0578 (<.0001)	0.0950
Trade & Industrials	0.0031 (<.0001)	0.0072 (0.0710)	0.0339 (<.0001)	0.2619	0.0027 (<.0001)	0.0094 (<.0001)	0.0142 (<.0001)	0.2282

Panel B: Post-Reform

	α_0	α_1	α_2	R^2	α_0	α_1	α_2	R^2
All stocks	0.0037 (<.0001)	0.0129 (<.0001)	0.0006 (0.7528)	0.1558	0.0036 (<.0001)	0.0033 (<.0001)	-0.0002 (0.8367)	0.0645
Financials	0.0018 (<.0001)	0.0088 (<.0001)	-0.0008 (0.8142)	0.1220	0.0017 (<.0001)	0.00354 (0.0003)	0.0019 (0.0845)	0.0591
Railways	0.0023 (0.0031)	0.0955 (<.0001)	0.0017 (0.7340)	0.4898	0.0020 (0.0718)	0.0161 (<.0001)	0.0021 (0.5289)	0.0816
Steamships	0.0051 (<.0001)	0.0468 (<.0001)	-0.0005 (0.9313)	0.2252	0.0046 (<.0001)	0.01318 (<.0001)	0.0030 (0.4086)	0.0841
Trade & Industrials	0.0062 (<.0001)	0.0050 (0.1838)	0.0077 (0.0753)	0.0223	0.0057 (<.0001)	0.0040 (0.0218)	0.0058 (0.0046)	0.0550

The table presents estimates from the following equation: $CSSD_{m,t} = \alpha_0 + \alpha_1 D^{DOWN} + \alpha_2 D^{UP} + e_t$
The equation is estimated separately for the sub-periods January 1865 – June 1893 and July 1893 – July 1914 for: all stocks listed on the St. Petersburg stock exchange; Financials; Railways; Steamships; and Trade & Industrials. P-values are estimated based on heteroscedasticity-autocorrelation corrected standard errors and are included in parentheses. $CSSD_{m,t}$ ($R_{m,t}$) is the monthly cross-sectional standard deviation of returns (average return) for the total market and each industry separately.