**APPENDICES: Results of Other Tests**

Reported here are empirical results that supplement the paper, “Investor Reactions to Legislative Liberalization and the Runup in British Share Prices, 1844 to 1845.” These consist of the following:

* Appendix 1: Validation of data in the Global Financial Data set.
* Appendix 2: Test of Robustness about Information Leakage. This examines the impact on the tests for significance of returns in the 18 event episodes from extending the window of observation from one day before the arrival of news (day T-1, as reported in Table 2 of the paper) to two days before (day T-2).
* Appendix 3: Test of Robustness about Zero Return Days. This examines the impact on the tests for significance of returns in the 18 event episodes from exclusion of securities with zero returns on 95 percent or more of the 498 trading days during the run-up, as compared to Table 2 of the paper that is based on the entire sample of 100 securities.
* Appendix 4: Cross-sectional Regression Analysis of Impact of Monetary Policy and Grain Prices on Daily Returns. This explores the possible impact of two alternative explanations for the run-up.
* Appendix 5: Test of Robustness of the Bootstrap Test. We test a relaxation in our approach to positioning event and non-event periods in the bootstrap test for significance of all episodes returns.

**Appendix 1: Validation of Data in the Global Financial Data Set.**

Some scholars have raised concerns about the reliability of Global Financial Data (GFD) price series. In contrast, other scholars including Goetzmann, Li, and Rouwenhorst (2005)[[1]](#footnote-1) and Goetzmann, Ibbotson, and Peng (2001) have used GFD data confidently after testing specific price series for accuracy. For example, Goetzmann, Li, and Rouwenhorst, compared “early series with other independent sources” and found that “GFD provides credible sources for most of the data series.” We examined samples of GFD returns in comparison with reports in *The Times of London* and *Course of the Exchange* and found immaterial variances.

In addition, we compared our dataset to the hand-collected returns data compiled in “Monthly Indices of Returns for the British Equity Market, 1825-70” by Graeme G. Acheson, Charles R. Hickson, John D. Turner and Qing Ye (2009). We were able to do this for the broad market and for three sectors which had a directly comparable sector in the monthly indices data of Acheson et al.—rail, banks, and insurance. First, we converted our market and sector daily series into monthly returns for January 1844 to July 1845. Then we computed the correlations of these monthly return series with those of the Acheson et al. series. As shown in Panel A (below), except for the Banks sector, the correlations with both the capital appreciation and total return series were generally above 0.76 and reached as high as 0.82 for the insurance sector. We consider these correlations to be reasonably high, given that our sample includes only firms with full returns over the analysis period. This restriction means that we drop new entrants and firms which exited the public markets during the period. As a final check, we applied a two-tail unequal-variances (heteroscedastic) t-test to compare the means of our sector returns and those in Acheson et al. All p-values are well above 0.05, so we fail to reject the null hypothesis that the two data series have equal mean returns at the five percent significance level. This is also true for the Banks sector, where the observed correlation between the two series is low.

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| **Table A1****Correlation and Test for Significance of Difference: Comparison of This Data Set with Acheson, Hickson, Turner, and Ye** |
| **Panel A: Correlations** |  |  | **Panel B: T-test p-values** |  |
| *Sector* | *Capital Appreciation Series* | *Total Return Series* |  | *Sector* | *Capital Appreciation Series* | *Total Return Series* |
|  *Market* |  0.71  |  0.72  |  | *Market* |  0.67  |  0.30  |
| *Rail* |  0.76  |  0.77  |  | *Rail* |  0.56  |  0.74  |
| *Banks* |  0.04  |  0.05  |  | *Banks* |  0.80  |  0.62  |
| *Insurance* |  0.82  |  0.82  |  | *Insurance* |  0.65  |  0.38  |

Considering precedential use of the GFD set in other research, of our own selective checking for accuracy of the data, and of correspondence with another prominent data set, we base our calculations on the GFD price series.

**Appendix 2: Test of Robustness about Information Leakage**

*The Times of London* reported on various occasions the allegations that news of government policy innovations had leaked to traders in advance of public announcements. Therefore, we repeated the analysis by enlarging the event episode to include one more day, starting from day T-2 rather than T-1.

**Table A2.1** gives the test of CERs vs RURs for comparison to Table 1 in the paper. Adding the one additional day (from T-1 to T-2) induces no material change from the results in Table 1. In both Table 1 and Table 2.1, the difference of event returns from non-event returns remains material and significant, and the bootstrap test finds a significant difference between the distributions of all event returns versus returns of the entire run-up.

 **Table A2.2** considers possible information leakage around the 18 legislative event episodes: an *increase* in returns due to adding one more day would be consistent with leakage. The table affords two main insights. First, in terms of statistical significance of CERs, Table A2.2 reveals only one *new* significant CER, that of the Metals Sector in March 1844 (line 2), which is consistent with information leakage. Of the 15 significant CERs in Table 2 of the paper, 10 remain significant after enlarging the window by one day, which suggests that for the five episodes that dropped in significance, the addition of one day merely adds noise, rather than information.

Second, a comparison of the significant railway sector CERs between Table 2 and Table A2.2 reveals increases of 0.50 percent in January 13-20, 1845 (line 11) when the Select Committee indicated a preference for incumbent railways, 0.38 percent in May 26-June 2, 1845 when Lord Russell declared that repeal of the Corn Laws would be a priority for the Liberal Party (line 16), 0.27 percent in March 4-8, 1844, with Peel’s first proposal of the Joint Stock Companies Act (line 2), and 0.11 percent on July 18-24, 1844 when the three major legislative initiatives gained affirmative votes in Parliament (line 6). These small increases imply some information leakage on day T-2.

Overall, these results are qualitatively consistent with the insights obtained from Tables 1 and 2 of the paper. The slightly larger CERs given in Table A2.2 are consistent with some leakage of information, though the effect on the size and significance of CERs reported here is not material.

**Table A2.1: Bootstrap Test for Event Periods Cumulative Returns Significance (starting at T-2)**

We test the robustness of the returns results using bootstrap methodology. For each market and return window, we compare the event cumulative observation period returns to a randomly drawn distribution of 100,000 cumulative returns of the same window length and from the full runup period, from each respective market. P-values are based on the position of the cumulative event returns in the top tail of the bootstrapped distributions. Thus, p<0.01 indicates that the event returns were above the 99th percentile of bootstrapped returns. This table reveals positive and significant returns at event dates associated with news regarding government policy innovations. The authors’ archival research identified event periods and non-event periods.



Note: § The Levene tests of the equality of variances between Event vs. Non-Event Episodes revealed insignificant differences for the returns series, except for the Market series. Therefore, our t-test for the returns assumes equal variances for all series, except the market.

**Table A2.2: Bootstrap Test for Event Periods Cumulative Returns Significance (starting at T-2)**

We test the robustness of the returns results using bootstrap methodology. For each market and return window, we compare the event cumulative observation period returns to a randomly drawn distribution of 100,000 cumulative returns of the same window length and from the full runup period, from each respective market. P-values are based on the position of the cumulative event returns in the top tail of the bootstrapped distributions. Thus, p<0.01 indicates that the event returns were above the 99th percentile of bootstrapped returns. This table reveals positive and significant returns at event dates associated with news regarding government policy innovations. The authors’ archival research identified event periods and non-event periods.



**Appendix 3: Test of Robustness Related to Securities with Extensive Zero Return Days**

Some securities in our sample reported material percentages of zero returns (in the paper, see Table 1 lines 4, 15, 26). Since archival sources did not report trading volume, we could not determine the extent of non-trading versus flat trading each day. Yet the zero returns present valuable information about possible investor responses to surprising news. Thus, we elected to report results based on the entire set of listed securities for the period. To the extent that some of these zero returns reflect the absence of trading, inclusion of these days biases returns toward zero.

We tested the robustness of our results in Tables 1 and 2 to the exclusion of securities with zero returns on 95 percent or more of the 498 trading days during the run-up. As a result of the exclusion, the sample declines from 100 securities to 53. The dropped firms make up 15.2% of the total sample market cap at the beginning of the runup and 12.3% at the end of it so although large in number they are smaller firms. The main sector of interest, Railways, loses very few firms and the broad results for all sectors are consistent with and without the removal of the infrequently trading firms.

**Table A3.1** replicates Table 1 of the paper, after the exclusion of securities with few non-zero returns. The significance test results in lines 35, 37, and 38 differ immaterially from those in Table 1 of the paper.

**Table A3.2** replicates Table 2 of the paper after exclusion of securities with few non-zero returns. days raised the event returns but did not alter the qualitative insights. Returns are generally higher after the exclusion, consistent with the intuition that securities with many zero-return days biases the results toward zero. The significance of CERs for the Market Composite, Railway, Bank, and Shipping Trade samples is unchanged. However, after exclusion, the Insurance Sector gains two significant events (lines 2 and 8) both of which are significant for other sectors and are pivotal events as discussed in the paper. Also, the Metals Sector gains one significant event (line 6), which is significant for the Railway sector as well.

In all, these results are qualitatively consistent with the insights obtained from Tables 1 and 2 of the paper.

**Table A3.1: Bootstrap Test Comparing Distributions of Event and Non-Event Returns After Exclusion of Securities with Extensive Zero Return Days**

We test the robustness of the returns results using bootstrap methodology. For each market and return window, we compare the event cumulative observation period returns to a randomly drawn distribution of 100,000 cumulative returns of the same window length and from the full runup period, from each respective market. P-values are based on the position of the cumulative event returns in the top tail of the bootstrapped distributions. Thus, p<0.01 indicates that the event returns were above the 99th percentile of bootstrapped returns. This table reveals positive and significant returns at event dates associated with news regarding government policy innovations. The returns are based on value-weighted average returns estimated by the authors from share prices provided by Global Financial Data. The authors’ archival research identified event periods and non-event periods.



Note: § The Levene tests of the equality of variances between Event and Non-Event Episodes revealed insignificant differences for the returns series. Therefore, our t-test assumes equal variances.

**Table A3.2: Distribution of Returns When Sample is Restricted to Exclude Securities With Returns on Less Than 5 Percent of Run-Up Days**

We test the robustness of the returns results using bootstrap methodology. For each market and return window, we compare the event cumulative observation period returns to a randomly drawn distribution of 100,000 cumulative returns of the same window length and from the full runup period, from each respective market. P-values are based on the position of the cumulative event returns in the top tail of the bootstrapped distributions. Thus, p<0.01 indicates that the event returns were above the 99th percentile of bootstrapped returns. This table reveals positive and significant returns at event dates associated with news regarding government policy innovations. The authors’ archival research identified event periods and non-event periods.



**Appendix 4 Test for Impact of Monetary Policy Change and Grain Price Movements**

To test for possible omitted variables for which the legislative events might proxy, we assessed two factors that received considerable comment in contemporary media:

* changes in monetary policy. Passage of the Bank Charter Act granted the Bank of England a broader mandate for commercial lending. In advance of passage, the BoE announced that it would substantially lower its base rate, which upon enactment it did, from four percent to 2.5 percent. The BCA also limited the BoE’s discounting of commercial loans to a formula linked to the bank’s reserves. Presumably material changes in reserves would influence investor anticipation of credit availability. Consistent with the research of Bernanke and Kuttner (2005) and Campbell, Quinn, Turner, and Ye (2018), we hypothesized that news of accommodative credit conditions (lower interest rates and greater credit availability because of higher BoE reserves) would be associated with positive returns to shareholders.
* changes in grain prices, which might affect the demand for grain and the transportation necessary to bring the grain to market. We hypothesized that low (high) grain prices would stimulate more (less) demand for grain and more (less) transportation necessary to move the grain to market. We focused particularly on sharp changes in daily grain prices (greater than two standard deviations).

In an ARIMA-ARCH-GARCH model, we regressed daily returns against the natural logs of interest rate changes, changes in BoE reserves, and changes in grain prices. None of the coefficients for independent variables was significant, though the signs were generally consistent with hypotheses and though the ARIMA, ARCH, and GARCH factors were significant, indicating strong serial correlation.

Given the findings of heteroskedasticity and autocorrelation, we fitted an ARIMA-ARCH-GARCH [3,0,3] model to the data. Accordingly, the regression estimates reported here derive from the following model:

(1) Rt = a + β1(LNBoERBt) + β2(BoEintt) + β3(LNWheatt) + et

Where Rt = Daily return on the value weighted returns on the portfolios of the market composite, and railways and banks sectors on day t.

LNWheatt = Natural logarithm of weekly posted wheat prices at day t.

LNBoERBt = Natural logarithm of weekly reserves of the Banking Department of the BoE at day t.

BoEint = BoE Bank Rate on day t.

The null hypothesis for all coefficients is: H0: β = 0.

The alternative hypotheses are:

H0: β1 > 0. This reflects the assumption of a direct relation between BoE reserve changes and returns to equity investors.

H0: β2 < 0. This reflects the assumption of an inverse relation between BoE interest rate changes and returns to equity investors.

H0: β3 < 0. Higher wheat prices are consistent with smaller quantities traded and thus are a proxy for food insecurity.

**Table A4** presents the estimated regression coefficients on Equation 1, where the dependent variables are the daily returns on the market composite sample and on the railways and banks industry sectors.[[2]](#footnote-2) The independent variables are the natural log of wheat prices, natural log of total reserves of the Bank of England, and the percentage bank rate—the correlation among these independent variables was small. The Wald Chi-square coefficient (line 14) is significant in the three estimated equations, indicating that the independent variables are collectively significant—though this derives from the momentum in returns (lines 5-12) rather than the three independent variables of interest.

The estimated coefficient for wheat prices (line 1) is positive in all cases, and significant only for the market composite portfolio. The estimated coefficient for the BoE’s Bank Rate (line 2) is uniformly negative, consistent with the research of Bernanke and Kuttner (2005) and Campbell, Quinn, Turner, and Ye (2018), though none of the estimates is significant. Finally, the estimated coefficient for the natural log of BoE reserves (line 3) is negative for the banks sector and positive for railways and the market composite—and in none of the estimates is the coefficient significant.

The general insignificance of estimates in lines 1 to 4 rejects hypotheses that the run-ups in returns for railways, banks, and the market composite portfolio were affected by variations in grain prices and monetary policy.

**Table A4: Estimated Regression Coefficients, Daily Returns Against Monetary and Grain Price Measures**

(1) Rt = a + β1(LNBoERBt) + β2(BoEintt) + β3(LNWheatt ) + et

Where Rt = Daily return on the value weighted returns on the portfolios of the market composite, and railways and banks sectors on day t.

LNWheatt = Natural logarithm of weekly posted wheat prices at day t.

LNBoERBt = Natural logarithm of weekly total reserves of the BoE at day t.

BoEintt = BoE Bank Rate on day t.



**Appendix 5 Test of Robustness of the Bootstrap Test.**

In the baseline Bootstrap test for the significance of all event episodes together (Table 1, line 38), we randomly position event and non-event period windows inside the full runup timeline. In the 100,000 simulations that comprise the test, we preserve the length of each event and non-event window that we observe in the data and place them randomly across the full runup period. We avoid placing event (non-event) episodes directly next to one another, as that would result in a higher-length continuous event (non-event) period and could potentially bias the test results due to the serial correlations among returns in the runup.

In Table A5 (line 2) we test the practical impact of this limitation, by having a completely random positioning of event and non-event periods among the runup timeline, including allowing for event (non-event) periods placed directly next to one another. This approach can result in the potential formation of higher-length “joint” event or non-event periods. The one-sided p-value of the bootstrap test for the Railways series, the only significant industry, increases only modestly from 0.009 to 0.015. This suggests that the “forced” flip restriction between event and non-event periods in the base Bootstrap test does not meaningfully affect our results.

**Table A5: Robustness test of the Bootstrap Test for Difference of All Event Period Returns Versus Cumulative Returns for the Run-Up**



Source: Authors’ analysis.

1. Please see bibliographical references listed in the paper. [↑](#footnote-ref-1)
2. For brevity, we do not report the estimated coefficients for the insurance, metals, and shipping and trade sectors, for which coefficients were insignificant. [↑](#footnote-ref-2)