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STOCK VOLATILITY AND THE GREAT DEPRESSION

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ABSTRACT

Stock volatility during the Great Depression was two to three times higher than any other period in American financial history. The period has been labelled a "volatility puzzle" because scholars have been unable to provide a convincing explanation for the dramatic rise in stock volatility (Schwert, 1989). We investigate the volatility puzzle during the period 1928-1938 using a new series of building permits, a forward-looking measure of economic activity. Our results suggest that the largest stock volatility spike in American history can be predicted by an increase in the volatility of building permit growth. Markets appear to have factored in a forthcoming economic disaster.

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Introduction

The annualized standard deviation of US stock returns during the Great Depression reached as high as 60 percent per annum, two to three times higher than any other period in American financial history. **Figure 1** shows that stock volatility during the Great Depression stands out even when compared to the volatility of market returns over a time span of more than 200 years (1802-2013) that includes the Great Recession. A convincing explanation of why stock volatility was so high during the Great Depression has eluded scholars.[1] This has led some studies to suggest that the "excessive volatility" of stock returns in the late 1920s and 1930s might be the result of a "Peso problem" or irrational behavior by investors (Shiller, 1981). In his seminal article *"Why Does Stock Volatility Change Over Time,"* Schwert (1989) analyzes stock return data for more than 100 years and finds that various macroeconomic and financial time series are unable to predict the high levels of stock volatility observed during the Great Depression and the 1930s. Schwert concludes that *"there is a volatility puzzle."* (Schwert, 1989; 1990b; Pagan and Schwert, 1990).

We break new ground in studying the volatility puzzle of the Great Depression. Specifically, we test the ability of building permits, a forward-looking measure of economic activity to predict stock volatility during the period 1928-1938. Building

[1] Mathy (2016) finds that the spikes in stock volatility during the Great Depression were generated by a series of discontinuous jumps that can be explained by banking crises, the end of the gold standard, and expectations regarding the outbreak of war in Europe. White (1990) is the classical reference on the Great Crash of 1929.

permits are well-known to academic and professional forecasters to be a forward-looking indicator of aggregate economic activity and stock volatility (Leamer, 2007; 2009; 2015; Flannery and Protopapadakis, 2002; Stock and Watson, 1993). Building and housing permits often show up as components of leading economic indicators (LEIs) produced by forecasters such as the Conference Board or as variables used to predict recessions (Stock and Watson, 1993; Leamer, 2007; 2009). Furthermore, the volatility of the growth rate of building permits is a measure of the uncertainty of a growth option that depends on the future expected rents from new commercial and residential buildings. For these reasons, the volatility of the growth rate of building permits is a proxy for macroeconomic risk that can lead firms to reduce or eliminate dividend payments to shareholders. Lower income for investors decreases aggregate consumption in some disaster models of asset pricing (e.g. Barro, 2006; Gabaix, 2012).

We supplement the building permit series with new data to examine the role of economic, financial, and political factors in predicting monthly US stock volatility for the period 1928-1938. First, we employ Graham, Leary, and Roberts' (2015) measure of financial leverage that is taken from the *Moody's Manuals*. Their series allows us to directly control for a fundamental explanatory variable of stock volatility. Second, we use a new series of junk bond yield spreads to test the importance of forward-looking interest rates in forecasting stock volatility.[2] Other forward-looking indicators such as the volatility of truck production and bank

[2] It is well-known in the forecasting literature that interest rate spreads are important leading indicators of economic downturns (see e.g. Stock and Watson, 1993; Estrella and Mishkin, 1998).

lending are used as explanatory variables to predict the standard deviation of stock returns. Third, we hand-collect data on important political events to construct a new database of political uncertainty. Measures of political conflict are used to test the Merton-Schwert hypothesis that the high levels of stock volatility during the Great Depression were driven by the rise of communism that threatened the future of market capitalism (Merton, 1987; Schwert, 1989). We convert Banks' (1976) *annual* database on riots, assassinations, anti-government demonstrations, and general strikes into a *monthly* measure to examine the relationship between stock volatility and political uncertainty.

Our empirical analysis suggests that stock volatility during the Great Depression can largely be explained by two variables: (1) financial leverage; and (2) the volatility of the growth rate in building permits. The two-variable specification along with historical lags of stock volatility account for about 73 percent of the movements in stock volatility for the entire sample period 1928-1938. **Figure 2** shows that the big volatility spike in the growth rate of building permits in early 1929 leads and predicts the largest stock volatility spike in American history. The simple model of stock volatility predicts the standard deviation of stock returns even better if we limit the sample period to just the Great Depression as defined by NBER recession dates. The R-squared for the Great Depression period is 85 percent.

The empirical results are robust to many different specifications. Except for the volatility of truck production (trucks are often used by the construction industry to help construct buildings), the macroeconomic and credit channel proxies do not significantly predict stock volatility during the Great Depression. We argue that the volatility puzzle of the Great Depression is largely solved by incorporating building permits, a forward-looking measure of aggregate economic activity, into a simple model of stock volatility.[3] Given the robustness of the baseline result, we then investigate the economic and financial factors that predict the volatility of building permits. There appears to be little evidence that macroeconomic or financial factors can predict the volatility of the forward-looking construction measure.

The paper begins with a discussion of the economic and financial data used in the study. This is followed by the empirical analysis of stock volatility. We then test the robustness of the baseline specifications. The empirical analysis concludes with a study of the role of economic and financial factors in predicting the volatility of the growth rate in building permits. The final section discusses the implications of the results and makes suggestions for future research.

I. Building Permits

We use the value of building permits, *"Permits"*, as a forward-looking indicator of economic activity. Building permits must be filed with local authorities before any construction can take place. The construction data are taken from various issues of *Dun and Bradstreet's Review*, a well-known monthly business and financial publication in the 1920s and 1930s. The forward-looking measure of economic activity is assembled from building inspector reports collected by the *F.W. Dodge*

[3] Leamer (2015, p. 43) argues that *"housing is the single most critical part of the U.S. business cycle, certainly in predictive sense and, I believe, also in a causal sense."*

Division, a *McGraw-Hill Information Systems Company*. *F.W. Dodge* also provided their data to the Bureau of Labor Statistics (BLS). The value of building permits is based on the cost of new commercial and residential buildings for 215 cities across the US.

Figure 3 plots the value of building permits from 1928-1938.[4] At the beginning of the sample period, building permits rose to a value of almost $350 million and then declined to $213 million by the start of 1929. Building permits increased to nearly $229 million in February, and to $372 million in March 1929. In April 1929, building permits rose to a level of almost $480 million. The rise represents a 62 percent increase over the previous year. The forward-looking economic measure fell to $260 million in May and to $218 million in June. One month before the Great Crash in October 1929, the value of building permits declined to $183 million. The value of building permits fell by more than 60 percent between April and September 1929.[5] The forward-looking construction measure remained quite low for the remainder of the sample period except for a couple of spikes at the end of the sample period.

The building permit spike in 1929 appears to be largely explained by an increase in the number of large buildings and planned skyscrapers in New York City. In Manhattan, 14 skyscrapers of 30 stories or higher were filed with the city in 1928. The number of skyscraper building permits increased to 52 in 1929 with most of the

[4] A consistent time series for building permits with 215 cities begins in 1927.
[5] Romer (1990) argues that the Great Crash increased uncertainty which led to a decline in the consumption and production of durable goods.

activity taking place at the beginning of the year.[6] **Figure 3** shows that the value of building permits in New York City rose dramatically from $29.6 million in January 1929 to more than $259.1 million in April. New York City building permits then abruptly fell to a value of $37.1 million in June. The large rise in building permits during 1929 disappears if the New York City filings are removed from the aggregate series.

The 1928-29 New York "skyscraper boom" saw the construction and completion of the Waldorf-Astoria and the Empire State Building (Barr, 2010). The latter was finished at half the expected cost of $25 million in 1931 because of the precipitous decline in economic activity from the Great Depression. Other (less high profile) skyscrapers included the National City Bank Building on 55 Wall Street between Hanover and William Streets. Overall, only 19 of the 52 planned skyscrapers in 1929 were ever built as construction spending tanked with the onset of the Great Depression (Gray, 2009).[7] Many builders decided not to exercise their option (building permit) to build a skyscraper. Alternatively, some entrepreneurs exercised only a fraction of their option by building a cheaper skyscraper as shown by the Empire State Building. Another alternative was to delay construction of the skyscraper because of poor economic conditions. The National City Bank Building was not completed until the 1940s.

Therefore, we use the volatility of building permit growth as a forward-looking measure of the uncertainty of a growth option that depends on expectations

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[6] Gray (2009); Barr (2010).

[7] For data and information on New York City skyscrapers, see Gray and Braley (2017).

of future rents from new commercial and residential buildings. For our purposes, the "skyscraper boom" observed in the building permit data is important given that some studies have found evidence that skyscraper completions peak right before the onset of a recession.[8]

II. Data

We use monthly data from January 1928 to December 1938 for the empirical analysis. We combine various sources to assemble a new database with economic, financial, and political variables to explain movements in stock volatility during the Great Depression.[9] For stock volatility, we calculate the monthly sample standard deviation of stock returns from daily data using CRSP.[10] Panel A of **Figure 4** shows the market capitalization of aggregate equity returns during the period 1928-1938. The market collapses with the Great Crash of 1929 and bottoms out in late 1932.

Leverage Data. The data on the market value of corporate leverage are taken from Graham, Leary, and Roberts (2015). The market value of leverage is calculated as *Debt/(Debt + Market Equity*) for non-financial firms. We transform the annual series of financial leverage into a monthly series by linear interpolation for the period 1928:M1-1938:M12. The measures of book and market leverage reported by Graham, Leary, and Roberts (2015) are reproduced in Panel B of **Figure 4.** *Book*

[8] Engelhardt and Thornton (2015) find that skyscraper height predicts business cycles. Barr (2010) and Barr, Mizrach, and Mundra (2015) find that skyscraper height does not Ganger-cause recessions.
[9] A description of the data sources is presented in Appendix A.
[10] See Schwert (1990a).

Leverage is relatively stable over the sample period compared to *Market Leverage* which shows large changes during the Great Depression (shaded area).[11]

Economic and Financial Data. We use a bank lending measure collected by the Federal Reserve and an index of new truck production as forward-looking economic indicators that might predict stock volatility.[12] Two yield spread measures are employed for the empirical analysis. First, the interest-rate differential between AAA corporate bonds and commercial paper is used to predict stock volatility. Then a junk bond yield spread for the interwar period constructed by Basile, Kang, Landon-Lane, and Rockoff (*forthcoming*) is incorporated into the baseline regression models. Data on coincident economic variables are also used to assess the importance of real factors in forecasting stock volatility. We utilize the Federal Reserve's series on retail sales and industrial production (IP) to estimate the volatility of the real sector.

Political Data. We construct a monthly version of Banks' (1976) annual *Cross-Polity Time-Series* for the US. The political database is widely used in economics, political science, and other social sciences. The annual database is converted into a monthly one using Banks' original sources and the search engine for the *ProQuest Historical New York Times*.[13] We follow the previous literature (e.g. Passarelli and Tabellini, *forthcoming*; Funke, Schularick and Trebesch, 2016) in our selection of conflict variables that proxy for political uncertainty. The four variables are: (1)

[11] *Book Leverage* is depicted for illustration purposes only. In our empirical analysis, we only use *Market Leverage* for being a key variable in stock volatility models.
[12] The bank lending measure is derived from reports of member banks to the Federal Reserve System.
[13] Appendix A has a detailed description of the sources used by Banks (1976).

Anti-Government Demonstrations; (2) *Assassinations*; (3) *General Strikes*; and (4) *Riots*. An *Anti-Government Demonstration* is any peaceful public gathering of at least 100 people for the primary purpose of displaying or voicing their opposition to government policies or authority (excluding anti-foreign nature demonstrations). The number of *Assassinations* is defined as a politically-motivated murder or attempted murder of a high government official or politician. A *General Strike* is a strike of 1,000 or more industrial or service workers that involves more than one employer and targets national government policies or authority. Finally, a *Riot* is a violent demonstration or clash of more than 100 citizens involving the use of physical force.[14] The specific events data are then summed up to form an aggregate ***"Politics"*** variable:

$$\textit{Politics} = \textit{Assassinations} + \textit{Anti-Govt. Demonstrations} + \textit{General Strikes} + \textit{Riots}$$

The descriptive statistics are reported in **Table 1.** The volatility of the economic and financial times series are much less for the entire sample period (Panel A) compared to the Great Depression (Panel B). Political variables are also more volatile in the Great Depression, which is consistent with the hypothesis that political conflict is correlated with the poor economic conditions of the Great Depression. **Figure 5** contains panels that show the monthly frequency for each of the different measures of political conflict. *Assassinations* were quite rare with only two instances in the sample. The most frequent events were *Anti-Government*

[14] Appendix A describes the methodology used to collect the political data.

Demonstrations, followed by *Riots* and *General Strikes*. *Riots* and *Anti-Government Demonstrations* also display greater frequency during the Great Depression sub-period.

III. Empirical Strategy

The first step in our empirical analysis is to extract a measure of volatility from the raw data. We estimate GARCH (1,1) models to construct estimates of the one-step ahead conditional standard deviation for several of the independent variables in the empirical analysis. To control for persistence in the mean of each series, we employ 12 lags of the dependent variable in the mean equation and estimate the system by Maximum Likelihood methods. We then proceed with our baseline empirical analysis of the determinants of stock volatility during the Great Depression.[15] The model can be written as follows:

$$\begin{aligned} Stock\ Vol_t = \beta_0 + \sum_{m=1}^{11} D_m + \sum_{p=1}^{7} \beta_{1,p} \cdot Stock\ Vol_{t-p} + \sum_{p=1}^{7} \beta_{2,p} \cdot Lev_{t-p} \\ + \sum_{p=1}^{7} \beta_{3,p} \cdot Permit\ Vol_{t-p} + \sum_{p=1}^{7} \beta_{4,p} \cdot Politics_{t-p} + \varepsilon_t \end{aligned} \tag{2}$$

where *Stock Vol* is our measure of stock market volatility (standard deviation of stock returns), D_m is a set of seasonal monthly dummies, *Lev* is the market value of aggregate corporate leverage, *Permit Vol* is the volatility of building permit growth

[15] We employ a methodology similar to Paye (2012).

estimated from a GARCH(1,1) model, *Politics* is the sum of the four measures of political conflict, and ε_t is a normally-distributed error term. A lag length of seven is chosen based on the Akaike Information Criterion (AIC).[16] We estimate the following OLS regression models using robust standard errors:

1. ***Autoregressive Model:*** a model that includes only the lags of stock volatility (*Stock Vol*) and seasonal dummies to measure how much of current volatility can be explained by historical volatility.
2. ***Pure Leverage Model:*** a model that adds the lags of financial leverage (*Lev*) to the initial *Autoregressive Model*. Financial leverage is widely considered a fundamental determinant of stock volatility.
3. ***Economic Model:*** a model focusing on the economic determinants of volatility. The economic specification includes financial leverage and the volatility of building permit growth (*Permit Vol*), a forward-looking measures of economic activity.
4. ***Political Model:*** a model that includes financial leverage and the political determinants of stock volatility to test the Merton-Schwert hypothesis.
5. ***Joint Economic-Political Model:*** a model combining the variables from the *Economic* and *Political* models.

We follow Schwert (1989;1990c) and several studies (e.g. Flannery and Protopapadakis, 2002; Elder, Miao and Ramchander, 2012; Fatum, Hutchinson and Wu, 2012; Paye, 2012), that assess models of financial volatility by comparing the R-squared of different specifications. For example, the *Economic Model* tests the

[16] As a robustness test, we also estimated stock volatility regressions using 12 lags of the independent variables (Schwert, 1989). The basic tenor of the results remains unchanged.

hypothesis that the volatility of the growth rate of building permits predicts stock volatility. If the forward-looking measure of economic activity is statistically significant and the R-squared for the model increases, the result might suggest that economic factors were important for explaining the high levels of stock volatility during the period 1928-1938. More importantly, if the R-squared of the building permit specification is even higher during the Great Depression subsample, then the finding would provide additional evidence that markets were concerned about a forthcoming economic disaster. We now turn to the empirical analysis.

IV. Results

A. Stock Volatility: Full Sample Period

Table 2 shows the results for the full sample period, 1928-1938. Column 1 reports the *Autoregressive Model*. Seven lags of historical volatility explain 60 percent of the standard deviation of stock volatility for the period 1928-1938. We next control for financial leverage. A higher ratio of the book value of debt relative to the market value of equity means that it is more difficult for the firm to pay off its debt obligations. Distressed firms or companies with a greater likelihood of default (high indebtedness) also mechanically have higher stock return volatility (Schwert, 1990b). Seven lags of leverage are then added to the baseline autoregressive specification. Column 2 shows that leverage is statistically significant at the one percent level. Leverage increases the explanatory power of the model from 60 to 68 percent.

The results of the forward-looking economic model appear in Column 3 of **Table 2**. The F-statistics for the volatility of building permit growth is significant at the one percent level. The building permit specification increases the R-squared by five percentage points to 73 percent. We follow-up the forward-looking economic model with a political model of stock volatility. The empirical analysis is reported in Column 4. The results show that the aggregate political measure is not significant at conventional levels.[17] The R-squared of the political measure only increases the fit of the model by three percentage points to 69 percent relative to the baseline model of historical lags of stock volatility and financial leverage. This is somewhat surprising given that some political events in the sample period were quite notable and widely reported in the press. For example, Anton Cermak, the Mayor of Chicago, was murdered in February 1933 even though the hit targeted President Franklin D. Roosevelt.[18] Senator Huey Long was killed in a shooting in September 1935, a year before the outspoken congressman planned to run for President of the United States against FDR.[19]

Finally, we combine the forward-looking economic model with the political specification in Column 5. The volatility of building permits remains statistically

[17] Voth (2002) finds that political variables explain a significant fraction of stock volatility using stock market data for a sample of 10 countries during the period 1919-1938. His analysis does not consider leverage, however.

[18] The front-page headlines of the *New York Times* read *"Cermak in Critical Condition at Hospital; 'Glad It Was I, Not You,' He Tells Roosevelt." New York Times*, February 16th, 1933.

[19] We also tested whether the Economic Policy Uncertainty (EPU) Index constructed by Baker, Bloom, and Davis (2016) could predict stock volatility during the Great Depression and 1930s. The EPU variable was not statistically significant. The results are available from the authors by request.

significant at the one percent level while the aggregate political variable is not significant at the five or ten percent level. The R-squared rises to 74 percent in the economic and political model of stock volatility. The forward-looking building permit variable is statistically significant in all specifications. Overall, the results suggest that the volatility of building permits had a larger impact on stock volatility than political factors.

The baseline results for the full sample period are then subjected to a battery of robustness checks. We test whether the volatility of retail sales, industrial production, inflation, value of construction contract growth, manufacturing hours, truck production growth, and the volatility of the growth rate of manufacturing hours can predict stock volatility. [20] The empirical results reported in **Table 3** show that economic variables cannot predict stock volatility except for the volatility of truck production growth. This is not surprising given that trucks are often used to transport materials to help build new commercial and residential structures.

Table 4 presents the empirical results of adding money and credit variables to the baseline regression of leverage and the volatility of building permit growth.[21] The volatility of M2 money growth, the interest-rate differential between Junk bonds and AAA corporate bonds, the spread between AAA corporate bonds and prime commercial paper, and the volatility of the growth rate of bank loans cannot predict stock volatility. The additional money and credit variables are not

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[20] Schwert (1989) uses the volatility of industrial production, money growth, interest rates, and inflation as economic variables to explain stock volatility. He does not incorporate building permits (as defined by *Dun and Bradstreet's Review*) into his models of stock volatility.

[21] For a discussion of financial factors during the Great Depression, see Calomiris (1993).

statistically significant in the stock volatility regressions. The volatility of the growth rate of building permits remains significant in all specifications.

We next assess the explanatory power of the *Economic Model* by examining the residuals from a stock volatility regression that includes financial leverage and the volatility of building permit growth (note: the model excludes historical lags of stock volatility).[22] Panel A of **Figure 6** shows the residual series along with 95 percent confidence intervals. The two-variable model predicts stock volatility quite well given the high level and persistence of the standard deviation of stock returns during the late 1920s and 1930s. The R-squared is about 61 percent for the two-variable specification.[23] There are only two outliers in the residual graph that are outside of the 95 percent confidence intervals. The first outlier is the largest stock volatility spike in US financial history. Even though the regression residual of the dramatic rise in stock volatility during 1929 is outside the 95 percent confidence bands, the two-variable regression model explains more than 50 percent of the volatility spike. The simple regression model significantly reduces the amplitude of the largest stock volatility spike in US history to a much lower level.

The stock volatility model also does a good job at predicting the second largest volatility spike in US history that occurred during the "recession within the Great Depression" of 1937-38. The regression residual of the 1937-38 downturn is just outside the 95 percent confidence intervals shown in Panel A of **Figure 6**.

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[22] The regression used to compute the residual series also contains monthly seasonal dummy variables.

[23] The regression table used to construct the residual graphs is available in the Online Appendix.

Finally, we run a 24-month rolling regression using only lags of leverage and the volatility of building permit growth as explanatory variables. **Figure 7** reports the R-squared for the rolling regressions using the aggregate building permit series and the aggregate building permit series excluding New York City. The R-squared of the rolling regression for the aggregate permit series is particularly high during the Great Depression, rising to more than 90 percent as the moving window begins to include data at the onset of the Great Depression. The R-squared during the Great Depression is much lower if the building permit series for New York City is not included in the empirical analysis. Following the Great Depression, the statistical fit of the two rolling regressions is less sensitive to the building series employed for the empirical analysis. The results suggest that the boom in New York City "skyscraper permits" is particularly important for predicting the onset of the Great Depression. Overall, we interpret the residuals analysis and rolling regressions as strong evidence that the volatility of building permit growth largely explains the "volatility puzzle" of the Great Depression.

B. Stock Volatility: The Great Depression Sub-sample

The rolling regressions suggest that the volatility of building permit growth was especially important for forecasting the onset of the Great Depression and the largest stock volatility spike in US history.[24] **Figure 8** shows that the volatility of

[24] On the real estate dynamics during the 1920s, see Brocker and Hanes (2014) and White (2014). Goetzmann (2010, 2016) also discusses the building boom of the early 1920s and its collapse.

the growth rate of building permits leads the Great Crash of 1929, the large rise in stock volatility, and the onset of the Great Depression.[25]

Table 5 reports the empirical results from the Great Depression period as defined by the NBER (1929:M8–1933:M3). Columns 1 and 2 report the results for the autoregressive and leverage models, respectively. Both the historical lags of volatility and leverage are statistically significant. Adding leverage to the historical lag model increases the R-squared from 42 to 63 percent. Column 3 shows the results for the economic model. The volatility of building permits is once again statistically significant at the one percent level. The R-squared strikingly rises 22 percentage points to a value of 85 percent when the building permit variable is added to the model. An interesting finding in Column (3) is that the sign on the lags of stock volatility changes from positive and statistically significant in Columns (1) and (2) to negative and statistically significant in Column (3). This suggests that the building permit variable "crowds out" historical lags of stock volatility.[26] In other words, the building permit variable is a more powerful predictor of stock volatility than historical lags of stock volatility during the Great Depression. To address the negative coefficient on historical lags of stock volatility, we also report the regression results using the natural logarithm of stock volatility in Column (3a). Again, the empirical results confirm the baseline results that the volatility of building permit growth is an important predictor of stock volatility.

[25]The finding is broadly similar to the well-known relationship between housing starts and the recent downturn of 2007-09 (Gjerstad and Smith, 2014; Leamer, 2015).

[26] The result also suggests that the building permit variable is multi-collinear with lags of historical volatility.

Column 4 reports the political model of stock volatility during the Great Depression. The political uncertainty variable is not significant at conventional levels. The R-squared rises from 63 percent in Column 2 to 68 percent in the political specification. Column 5 of **Table 5** presents the empirical results of the Great Depression period for the economic-political model. The volatility of building permit growth is statistically significant at the one percent level, while the political conflict variable is not significant at conventional levels. The R-squared rises to 88 percent in the economic-political model. The results from the Great Depression sub-sample period suggest that the volatility of building permit growth predicts stock volatility even better under more severe economic conditions.[27]

We examine the regression residuals for the Great Depression sub-sample. Panel B of **Figure 6** presents the regression residuals calculated from a regression of stock volatility on lags of financial leverage and the volatility of building permit growth (note: the model excludes lags of historical volatility). The R-squared for the residual regression is almost 72 percent.[28] The regression residuals are shown with 95 percent confidence intervals, indicating that the regression residuals are not statistically significant except for one month in 1931. The Great Depression sub-sample provides even stronger evidence that the volatility of building permit growth

[27] Robustness checks also show that the volatility of truck production growth is not a significant predictor of stock volatility for the Great Depression sub-sample, even though it is significant in the full sample. The results are available from the authors upon request.
[28] We do not include monthly seasonal dummy variables in the Great Depression sub-sample given the short time period.

largely explains the "stock volatility puzzle" of the Great Depression.[29] Given the importance of the construction measure in forecasting stock volatility during the Great Depression, a natural follow-up question is: what factors explain the volatility of building permits? We examine this issue in the next section.

C. What drives the Volatility of the Growth Rate in Building Permits?

We estimate several regressions to examine the factors that predict the volatility of building permit growth for the sample period 1928-1938. The dependent variable for the regressions is the conditional standard deviation of the growth rate of building permits (*Permit Vol*). We consider three possible channels that could drive the volatility of the growth rate of building permits: (1) *Real Channel* (retail sales volatility and the volatility of truck production growth); (2) *Monetary Channel* (money growth volatility); and the (3) *Credit Channel* (Junk Bond -AAA Corporate Bond; AAA Corporate Bond-Prime Commercial Paper Spread; Volatility of bank loan growth). The volatility of each variable is estimated using a standard GARCH(1,1) model with robust standard errors, except for the two credit spreads which are included directly in the model as in Schwert (1989). A lag length of 7 is employed for each independent variable. We regress the volatility of the growth rate of building permits on each of the three channels.

[29] As an additional robustness check, we replaced our stock volatility measure (the standard deviation of monthly stock returns calculated from daily returns) with the historical News-Implied Volatility Index (NVIX) constructed by Manela and Moreira (2017). The volatility of the growth rate of building permits is also a significant predictor of implied volatility as proxied by the NVIX for the Great Depression sub-sample, but not for the full sample period. These results are available from the authors upon request.

The empirical results are reported in **Table 5**. Column 1 shows the regression using only historical lags of the volatility of building permit growth. The F-stat for the historical lags of building permit growth volatility is significant at the ten percent level, and the R-squared is only 24 percent for the baseline regression. Next, we add the volatility of retail sales to the baseline specification (Column 2). The volatility of retail sales is not statistically significant at conventional levels. Historical lags of the volatility of the growth rate of building permits are also not statistically significant at the five or ten percent level. The R-squared for the predictive regression model is 27 percent.

We next replace the volatility of the growth rate of retail sales with the volatility of truck production growth. Column 3 reports that truck production growth volatility predicts the volatility of building permit growth at the 10 percent level of significance. The R-squared for the regression is 40 percent for the truck specification. Column 4 presents the results for the monetary model. The volatility of monetary growth (M2) can predict the volatility of building permit growth at the five percent level. The R-squared is 26 percent and is only marginally higher than the baseline specifications that include historical lags of building permit volatility.

The results for the credit channel models are presented in Columns 5, 6, and 7. In the junk bond specification, both the historical lags of the dependent variable and the credit measure are not significant at conventional levels. The R-squared for the high-risk credit channel model is 26 percent. As for the interest-rate differential between corporate bonds and commercial paper, the yield spread does not predict the building permit variable as shown in Column 6. The R-squared for the AAA corporate and commercial paper model is 29 percent. Column 7 presents the results of the bank loan specification. The volatility of bank lending growth does not significantly predict the volatility of building permit growth. Finally, we combine the independent variables from the monetary model, the real sector specification, and the credit channel regressions. The results of the fully specified model appear in Column 6. The historical lags of building permit growth volatility and the other variables are not statistically significant with the exception of the truck variable (that is related to building construction as discussed earlier). The truck variable is significant at the 10 percent level and the R-squared is 62 percent for the kitchen sink model that includes six variables. The all-channel model also suggests that the volatility of money growth is not robust in predicting the volatility of building permit growth. Overall, we find little evidence that standard economic and financial variables can predict the volatility of the growth rate of building permits.

V. Concluding Remarks

Were the high levels of stock volatility during the Great Depression really a puzzle? We do not think so. We believe that the puzzle is largely resolved by incorporating the volatility of building permit growth, which is a measure of the uncertainty of a growth option that depends on future expected building rents, into a model of stock volatility. The forward-looking measure is supplemented with new data on financial leverage and political uncertainty. The volatility of the growth rate of building permits predicts a significant portion of stock volatility for the entire sample period. More importantly, the forward-looking measure of economic activity predicts stock volatility *even better* during the Great Depression as defined by NBER recession dates. This is shown by an R-squared of 85 percent for a simple two-variable model of stock volatility (along with historical lags of stock volatility). Moreover, even in a model without the historical lags of stock volatility, building permit growth and financial leverage predict stock volatility with an R-squared of over 70 percent. Overall, we find evidence that the leverage and building permit specification can predict the largest stock volatility spike in US financial history, and that the results are robust to a variety of different specifications.

Given the importance of the volatility of building permits, we explored the determinants of the volatility of building permit growth. We found weak evidence that standard economic and financial measures can forecast the volatility of the growth option. In sum, our analysis suggests that future research might test whether forward-looking economic measures such as building permits or housing starts have greater explanatory power for predicting stock volatility during a period of severe economic and financial stress. It might be particularly interesting to see if the volatility of building permit growth can forecast stock volatility in other turbulent periods such as the 2008 Great Recession where housing played an important role.

REFERENCES

Baker, Scott R., Nicholas Bloom, and Steven J. Davis (2016). Measuring Economic Policy Uncertainty. *Quarterly Journal of Economics* 131(4), 1593-1636.

Banks, Arthur S. (1976). *Cross-National Time Series, 1815-1973*. In: Inter-University Consortium for Political and Social Research, No. 7412.

Barr, Jason (2010). Skyscrapers and the skyline: Manhattan, 1895–2004. *Real Estate Economics*, 38(3), 567-597.

Barr, Jason, Bruce Mizrach, and Kusum Mundra (2015). Skyscraper height and the business cycle: separating myth from reality. *Applied Economics* 47(2): 148-160.

Barro, Robert J. (2006). Rare disasters and asset markets in the twentieth century. *Quarterly Journal of Economics*, *121*(3), 823-866.

Basile, Peter F., Sung Won Kang, John Landon-Lane, and Hugh Rockoff (forthcoming). An Index of the Yields of Junk Bonds: 1910-1955. *Journal of Economic History*.

Brocker, Michael and Christopher Hanes (2014). The 1920s Real Estate Boom and the Downturn of the Great Depression: Evidence from City Cross-Sections. In: White, Eugene N., Kenneth Snowden, and Price Fishback (editors), *Housing and Mortgage Markets in Historical Perspective*, p.161-201. University of Chicago Press and National Bureau of Economic Research.

Calomiris, Charles W. (1993) Financial Factors in the Great Depression. *Journal of Economic Perspectives*, 7(2), 61-85.

Elder, John, Hong Miao, and Sanjay Ramchander (2012). Impact of macroeconomic news on metal futures. *Journal of Banking & Finance* 36(1), 51-65.

Engelhardt, Lucas, and Mark Thornton (2015). "Skyscraper Height and the Business Cycle: Separating Myth from Reality, a Comment," Mises Institute Working Paper 0017.

Estrella, Arturo and Frederic S. Mishkin (1998). Predicting US recessions: Financial variables as leading indicators. *Review of Economics and Statistics*, 80(1), 45-61.

Fatum, Rasmus, Michael Hutchison, and Thomas Wu (2012). Asymmetries and state dependence: The impact of macro surprises on intraday exchange rates. *Journal of the Japanese and International Economies* 26(4): 542-560.

Flannery, Mark J. and Aris A. Protopapadakis. (2002). Macroeconomic Factors do Influence Aggregate Stock Returns. *Review of Financial Studies* 15(3):751-782.

Friedman, Milton and Anna J. Schwartz. (1963). *A Monetary History of the United States*. Princeton: Princeton University Press.

Funke, Manuel, Moritz Schularick, and Christoph Trebesch (2016). Going to extremes: Politics after financial crises, 1870–2014. *European Economic Review* 88, 227-260.

Gabaix, Xavier (2012). Variable Rare Disasters: An Exactly Solved Framework for Ten Puzzles in Macro-Finance. *Quarterly Journal of Economics*, *127*(2), 645-700.

Gjerstad, Steven D. and Vernon L. Smith (2014). *Rethinking housing bubbles: The role of household and bank balance sheets in modeling economic cycles*. Cambridge University Press.

Goetzmann, William N. (2016). *Money changes everything: How finance made civilization possible*. Princeton University Press.

Goetzmann, William N. and Frank Newman (2010). Securitization in the 1920s. NBER Working Paper #15650.

Graham, John R., Mark T. Leary, and Michael R. Roberts (2015). A Century of Capital Structure: The Leveraging of Corporate America. *Journal of Financial Economics*, 118, 658-683.

Gray, Christopher (2009). Ghost Buildings of 1929. *The New York Times,* April 23, 2009. http://www.nytimes.com/2009/04/26/realestate/26scapes.html. Access date: June 6, 2017.

Gray, Christopher, and Suzanne Braley (2017). The Building Permits Database for New York City, 1900-1986. Office for Metropolitan History. http://www.metrohistory.com/searchfront.htm. Access date: June 18, 2017.

Leamer, Edward E. (2007) Housing *is* the business cycle. *Proceedings of the Jackson Hole Economic Policy Symposium*. Federal Reserve Bank of Kansas City.

Leamer, Edward E. (2009). *Macroeconomic Patterns and Stories*. Berlin: Springer-Verlag.

Leamer, Edward E. (2015). Housing *really is* the business cycle: What survives the lessons from 2008-09? *Journal of Money, Credit, and Banking* 47(1), 43-50.

Manela, Asaf and Alan Moreira (2017). News-Implied volatility and disaster concerns. *Journal of Financial Economics,* 123(1), 137-162.

Mathy, Gabriel. (2016). Stock Volatility, Returns Jumps, and Uncertainty Shocks during the Great Depression. *Financial History Review*, 23(2), 165-192.

Merton, Robert C. (1987). On the Current State of the Stock Market Rationality Hypothesis. In: R. Dornbusch, S. Fischer and J. Bossons (editors), *Macroeconomics and Finance: Essays in Honor of Franco Modigliani*. Cambridge: MIT Press.

Pagan, Adrian R. and G. William Schwert (1990). Alternative Models for Conditional Stock Volatility. *Journal of Econometrics* 45, 267-290.

Passarelli, Francesco, and Guido Tabellini (forthcoming). Emotions and political unrest. *Journal of Political Economy*.

Paye, Bradley S. (2012). Déjà vol': Predictive Regressions for Aggregate Stock Market Volatility using Macroeconomic Variables. *Journal of Financial Economics* 106(3), 527–546.

Romer, Christina D. (1990). The Great Crash and the Onset of the Great Depression. *Quarterly Journal of Economics 105*(3), pp.597-624.

Schwert, G. William (1989). Why Does Stock Volatility Change Over Time? *Journal of Finance*, *44*(5), 1115-1153.

Schwert, G. William (1990a). Indexes of US Stock Prices from 1802 to 1987. *Journal of Business*, *63*(3).

Schwert, G. William (1990b). Stock Market Volatility. *Financial Analysts Journal* 46, 23-34.

Schwert, G. William (1990c). Stock returns and real activity: A century of evidence. *Journal of Finance*, 45(4), 1237-1257.

Shiller, Robert J. (1981). The use of volatility measures in assessing market efficiency. *Journal of Finance*, 36(2), 291-304.

Stock, James H., and Mark W. Watson (1993). A procedure for predicting recessions with leading indicators: econometric issues and recent experience. In: Stock, James H. and Mark W. Watson (editors), *Business Cycles, Indicators and Forecasting*. University of Chicago Press, 95-156.

Voth, Hans-Joachim (2002). Stock price volatility and political uncertainty: Evidence from the interwar period. *Centre for Economic Policy Research, CEPR Discussion Paper,* n. 3254.

White, Eugene N. (1990). The Stock Market Boom and Crash of 1929 Revisited. *Journal of Economic Perspectives*, 4(2), 67-83.

White, Eugene N. (2014). Lessons from the Great Real Estate Boom of the 1920s. In: White, Eugene N., Kenneth Snowden, and Price Fishback (editors), *Housing and Mortgage Markets in Historical Perspective*, p.115-158. University of Chicago Press and National Bureau of Economic Research.

Table 1. Summary Statistics

Panel A. *Full Sample (1928:M1–1938:M12)*

							Percentile, conditional on non-zero			
Variable	**Mean**	**Median**	**Std. Dev.**	**N. Obs.**	**Min**	**Max**	**10th**	**25th**	**75th**	**90th**
Stock Return Vol	0.017	0.014	0.009	132	0.005	0.049	0.007	0.010	0.022	0.031
Market Value of Leverage	14.606	12.236	6.155	132	7.648	27.093	9.326	10.222	16.086	25.918
Building Permit Vol	0.019	0.169	0.048	132	0.155	0.439	0.157	0.160	0.196	0.226
Assassinations	0.015	0.000	0.123	132	1	1	1	1	1	1
General Strikes	0.046	0.000	0.244	132	1	2	1	1	1	2
Riots	0.435	0.000	0.745	132	1	3	1	1	2	2
Anti-Govt. Demonstrations	0.397	0.000	0.883	132	1	6	1	1	2	2
Total Political Events	0.908	0.000	1.267	132	1	8	1	1	2	3

Panel B. *Great Depression Sub-sample (1929:M8–1933:M3)*

							Percentile, conditional on non-zero			
Variable	**Mean**	**Median**	**Std. Dev.**	**N. Obs.**	**Min**	**Max**	**10th**	**25th**	**75th**	**90th**
Stock Return Vol	0.023	0.021	0.011	44	0.007	0.049	0.009	0.013	0.028	0.040
Market Value of Leverage	21.055	25.918	6.052	44	11.830	27.093	11.830	16.086	27.092	27.092
Building Permit Vol	0.093	0.087	0.018	44	0.076	0.156	0.079	0.081	0.099	0.115
Assassinations	0.022	0.000	0.015	44	1	1	1	1	1	1
General Strikes	0.066	0.000	0.252	44	1	1	1	1	1	1
Riots	0.755	1.000	0.933	44	1	3	1	1	2	3
Anti-Govt. Demonstrations	0.578	0.000	0.965	44	1	5	1	1	2	2
Political Events	1.422	1.000	1.322	44	1	5	1	1	3	3

Table 2. Determinants of Stock Market Volatility, Full Sample (1928:M1-1938:M12)

The *Autoregressive Model* contains 7 lags of the standard deviation of stock returns. The *Pure Leverage Model* augments the *Autoregressive Model* with 7 lags of *Lev* (Market Leverage). The *Economic Model* adds *Permit Vol* (estimated Volatility of Building Permits Growth Rate) to the *Pure Leverage Model*. The *Political Model* combines the *Pure Leverage Model* with 7 lags of *Lev* (Market Leverage) and 7 lags of *Politics* (Sum of the following political events that proxy for Political Uncertainty: *Assassinations*, *General Strikes*, *Riots*, and *Anti-Government Demonstrations*). The *Economic-Political Joint Model* adds the variables from the *Economic and Political Models*. All specifications include seasonal monthly dummies. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

Dependent Variable: Stock Volatility

Full Sample (1928:M1-1938:M12)		**[1]** Autoregressive Model	**[2]** Pure Leverage Model	**[3]** Economic Model	**[4]** Political Model	**[5]** Economic-Political Joint Model
Lags of Variable:		$R^2 = 0.60$	$R^2 = 0.68$	$R^2 = 0.73$	$R^2 = 0.69$	$R^2 = 0.74$
Stock Vol	Sum Coefficients	0.843	0.514	0.453	0.519	0.418
(Std. Dev. of Stock Returns)	F-Test Statistic	157.91	40.50	42.19	30.89	36.15
	p-value	0.000***	0.000***	0.000***	0.000***	0.000***
Lev	Sum Coefficients	-	0.052	0.058	0.052	0.056
(Market Leverage)	F-Test Statistic	-	32.72	24.98	32.79	25.55
	p-value	-	0.000**	0.000***	0.000**	0.000***
Permit Vol	Sum Coefficients	-	-	0.046	-	0.055
(Building Permit Growth Volatility)	F-Test Statistic	-	-	22.52	-	17.54
	p-value	-	-	0.002***	-	0.014**
Politics	Sum Coefficients	-	-	-	0.000	0.001
(Sum of Political Conflict Variables)	F-Test Statistic	-	-	-	4.92	2.98
	p-value	-	-	-	0.670	0.887
Seasonal Dummies		YES	YES	YES	YES	YES
N. Observations		132	132	132	132	132

Table 3. Robustness: Real Activity and Inflation Indicators
Dependent Variable: Stock Volatility

Full Sample (1928:M1-1938:M12)		**[1]**	**[2]**	**[3]**	**[4]**	**[5]**	**[6]**
		Retail Sales	Industrial Production	Inflation (PPI)	Trucks Production	Building Contracts	Mfg. Hours
Lags of Variable:		$R^2 = 0.75$	$R^2 = 0.74$	$R^2 = 0.74$	$R^2 = 0.76$	$R^2 = 0.73$	$R^2 = 0.75$
Stock Vol	Sum Coefficients	0.459	0.446	0.363	0.314	0.453	0.413
(Std. Dev. of Stock Returns)	F-Test Statistic	31.08	33.60	31.46	33.36	36.99	38.21
	p-value	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Lev	Sum Coefficients	0.058	0.058	0.068	0.072	0.055	0.061
(Market Leverage)	F-Test Statistic	26.46	21.30	22.85	25.56	21.05	24.36
	p-value	0.000***	0.003***	0.002***	0.001***	0.004***	0.001***
Permits Vol	Sum Coefficients	0.048	0.058	0.060	0.050	0.054	0.044
(Building Permit Growth Vol)	F-Test Statistic	21.76	16.25	21.04	30.66	20.40	24.81
	p-value	0.003***	0.023**	0.004***	0.000***	0.005***	0.000***
Retail Sales Vol	Sum Coefficients	0.000	-	-	-	-	-
(Retail Sales Growth Volatility)	F-Test Statistic	10.29	-	-	-	-	-
	p-value	0.173	-	-	-	-	-
IP Vol	Sum Coefficients	-	-0.019	-	-	-	-
(Ind. Prod. Growth Volatility)	F-Test Statistic	-	5.84	-	-	-	-
	p-value	-	0.558	-	-	-	-
PPI Vol	Sum Coefficients	-	-	0.008	-	-	-
(Inflation Volatility)	F-Test Statistic	-	-	4.89	-	-	-
	p-value	-	-	0.674	-	-	-
Truck Vol	Sum Coefficients	-	-	-	0.020	-	-
(Truck Production Growth Vol)	F-Test Statistic	-	-	-	17.51	-	-
	p-value	-	-	-	0.014***	-	-
Building Contract Vol	Sum Coefficients	-	-	-	-	-0.010	-
(Building Contract Growth Vol)	F-Test Statistic	-	-	-	-	4.11	-
	p-value	-	-	-	-	0.767	-
Mfg. Hours Vol	Sum Coefficients	-	-	-	-	-	-0.025
(Manufacturing Hours Growth Vol)	F-Test Statistic	-	-	-	-	-	9.67
	p-value	-	-	-	-	-	0.208
Seasonal Dummies		YES	YES	YES	YES	YES	YES
N. Observations		132	132	132	132	132	132

Table 4. Robustness: Money and Credit Indicators
Dependent Variable: Stock Volatility

Full Sample (1928:M1-1938:M12)		[1]	[2]	[3]	[4]
		Money (M2) Supply Growth	Junk-AAA Spread	AAA-CP Spread	Bank Loan Growth
Lags of Variable:		$R^2 = 0.74$	$R^2 = 0.74$	$R^2 = 0.74$	$R^2 = 0.76$
Stock Vol	Sum Coefficients	0.441	0.510	0.442	0.403
(Std. Dev. of Stock Returns)	F-Test Statistic	37.03	42.78	40.92	30.30
	p-value	0.000***	0.000***	0.000***	0.000***
Lev	Sum Coefficients	0.056	0.078	0.061	0.060
(Market Leverage)	F-Test Statistic	19.69	19.79	22.02	21.99
	p-value	0.006***	0.001***	0.003***	0.002***
Permit Vol	Sum Coefficients	0.052	0.059	0.044	0.085
(Building Permit	F-Test Statistic	19.69	19.79	17.30	12.63
Growth Volatility)	p-value	0.006***	0.006***	0.002***	0.081*
M2 Vol	Sum Coefficients	-0.941	-	-	-
(Money Supply Growth Volatility)	F-Test Statistic	4.60	-	-	-
	p-value	0.709	-	-	-
Junk-AAA Spread	Sum Coefficients	-	0.000	-	-
(Junk Bond Spread vs.	F-Test Statistic	-	8.48	-	-
AAA Corporate Bond)	p-value	-	0.292	-	-
AAA Corporate-CP Spread	Sum Coefficients	-	-	0.000	-
(AAA Corporate-Price Commercial	F-Test Statistic	-	-	3.17	-
Paper)	p-value	-	-	0.869	-
Member Bank Loan Vol	Sum Coefficients	-	-	-	0.043
(Bank Loan Growth Volatility)	F-Test Statistic	-	-	-	9.62
	p-value	-	-	-	0.211
Seasonal Dummies		YES	YES	YES	YES
N. Observations		132	132	132	132

Table 5. Determinants of Stock Market Volatility, Great Depression Sub-sample (1929:M8-1933:M3)

The *Autoregressive Model* contains 7 lags of the standard deviation of stock returns. The *Pure Leverage Model* augments the *Autoregressive Model* with 7 lags of *Lev* (Market Leverage). The *Economic Model* adds *Permit Vol* (estimated Building Permit Growth Volatility) to the *Pure Leverage Model*. The *Political Model* combines the *Pure Leverage Model* with 7 lags of *Lev* (Market Leverage) and 7 lags of *Politics* (Sum of the following political events that proxy for Political Uncertainty: *Assassinations*, *General Strikes*, *Riots*, and *Anti-Government Demonstrations*). The *Economic-Political Joint Model* adds the variables from the *Economic and Political Models*. All specifications include seasonal monthly dummies. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

Dependent Variable: Stock Volatility

Great Depression Subsample (1929:M8-1933:M3)		**[1]**	**[2]**	**[3]**	**[3b]**	**[4]**	**[5]**
		Autoregressive Model	Pure Leverage Model	Economic Model	Economic Model (All Variables in Logs)	Political Model	Economic-Political Joint Model
Lags of Variable:		$R^2 = 0.40$	$R^2 = 0.61$	$R^2 = 0.85$	$R^2 = 0.86$	$R^2 = 0.68$	$R^2 = 0.88$
Stock Vol	Sum Coefficients	0.664	0.049	-0.649	-0.625	0.053	-0.696
(Std. Dev. of Stock Returns)	F-Test Statistic	29.29	36.77	25.23	24.72	16.26	27.28
	p-value	0.000***	0.000***	0.001***	0.001***	0.023**	0.000***
Lev	Sum Coefficients	-	0.065	0.168	1.640	0.030	0.162
(Market Leverage)	F-Test Statistic	-	211.30	90.37	81.79	17.67	44.41
	p-value	-	0.000**	0.000***	0.000***	0.014**	0.000**
Permit Vol	Sum Coefficients	-	-	0.281	2.213	-	0.296
(Building Permit	F-Test Statistic	-	-	33.02	31.60	-	24.04
Growth Volatility)	p-value	-	-	0.000***	0.000***	-	0.001***
Politics	Sum Coefficients	-	-	-	-	0.007	0.001
(Sum of Political Variables)	F-Test Statistic	-	-	-	-	5.73	3.64
	p-value	-	-	-	-	0.572	0.820
Seasonal Dummies		NO	NO	NO	NO	NO	NO
N. Observations		44	44	44	44	44	44

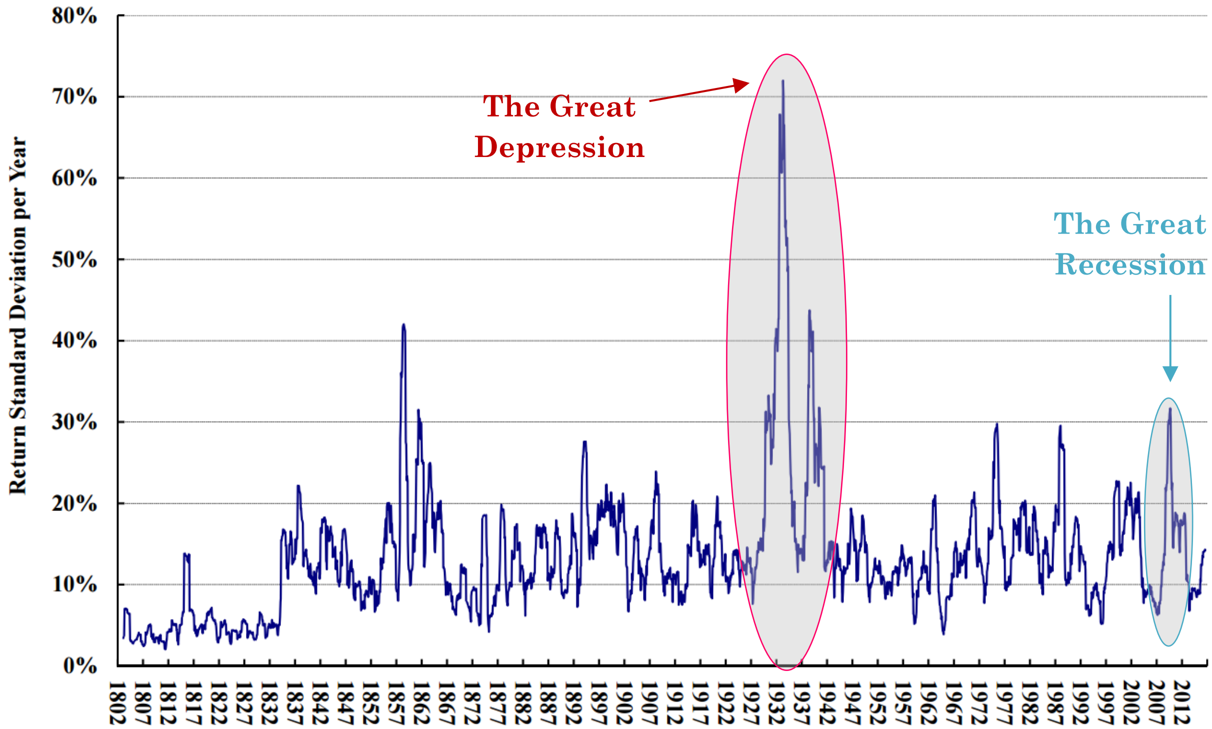
Table 6. The Determinants of Building Permit Growth Volatility (1928:M1-1938:M12)

The *Autoregressive Model* has 7 lags of Building Permit Growth Volatility (*Permit Vol*). Each additional specification augments the Autoregressive model with one variable of interest. Columns 2 and 3 show real side variables (*Real Channel:* retail sales volatility and truck production growth volatility); column 4 tests the *Monetary Channel* (M2 growth volatility); columns 5 to 7 test the *Credit Channel* (Junk *vs.* AAA Corporate Bond Spread, AAA Corporate vs. Prime Commercial Paper Spread, and Bank Loan Growth Volatility). Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

Dependent Variable: Volatility of Building Permit Growth

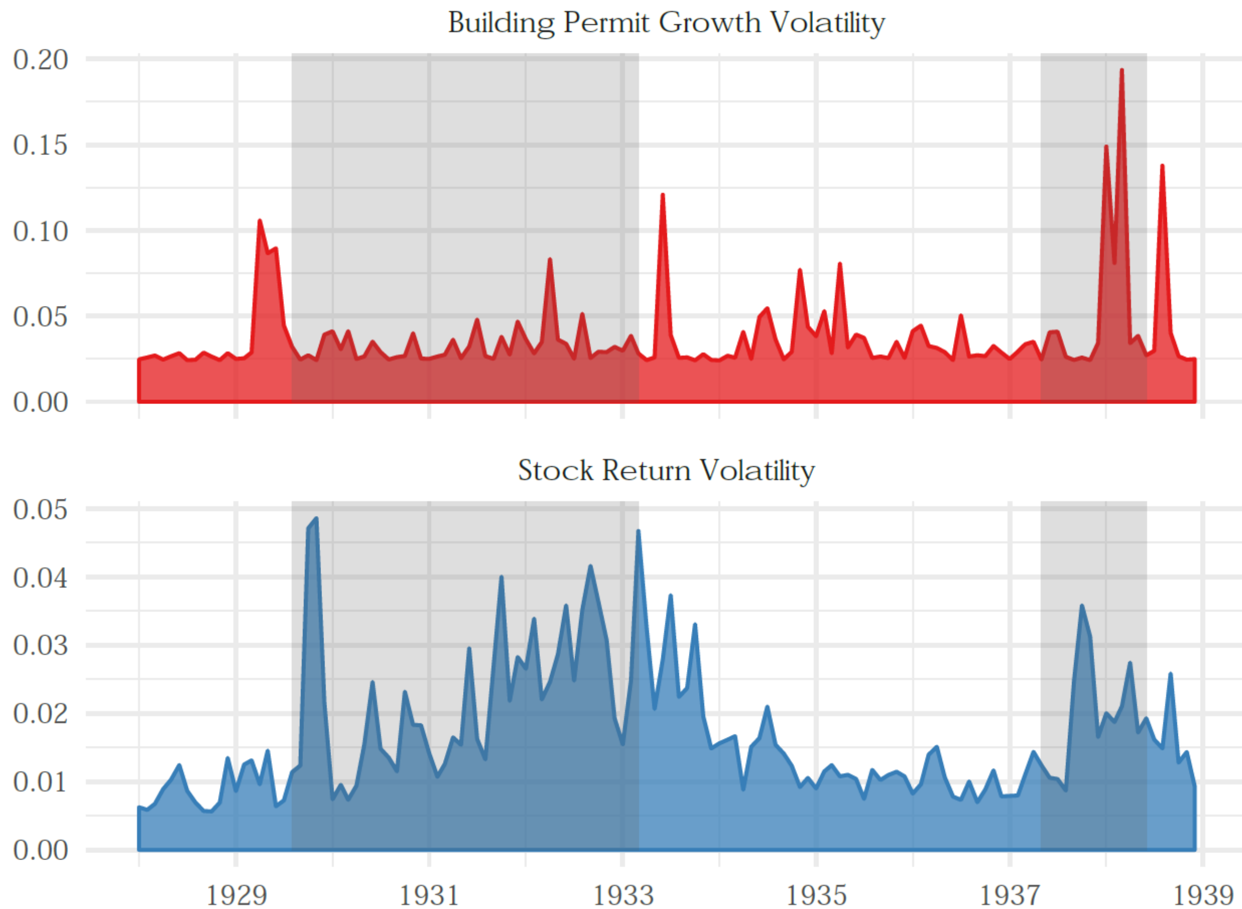
Full Sample (1928:M1-1938:M12)		**[1]**	**[2]**	**[3]**	**[4]**	**[5]**	**[6]**	**[7]**	**[8]**
		AR Model	Real Channel: Retail Sales	Real Channel: Trucks Production	Monetary Channel: M2	Credit Channel: Junk Spread	Credit Channel: AAA-CP Spread	Credit Channel: Bank Loan	All Channels
Lags of Variable:		$R^2 = 0.22$	$R^2 = 0.26$	$R^2 = 0.40$	$R^2 = 0.26$	$R^2 = 0.25$	$R^2 = 0.27$	$R^2 = 0.32$	$R^2 = 0.62$
Permit Vol	Sum Coeff.	0.428	0.450	0.510	0.446	0.407	0.434	0.355	0.229
(Building Permit	F-Test Stat.	14.11	11.13	14.54	15.62	12.60	16.38	10.11	6.11
Growth Volatility)	p-value	0.049**	0.133	0.042**	0.028**	0.083*	0.022**	0.182	0.527
Retail Sales Vol	Sum Coeff.	-	0.006	-	-	-	-	-	0.004
(Retail Sales Volatility)	F-Test Stat.	-	5.20	-	-	-	-	-	6.73
	p-value	-	0.636	-	-	-	-	-	0.458
Truck Growth Vol	Sum Coeff.	-	-	0.113	-	-	-	-	0.152
(Truck Production	F-Test Stat.	-	-	12.46	-	-	-	-	12.34
Growth Volatility)	p-value	-	-	0.086*	-	-	-	-	0.090*
Money Growth Vol	Sum Coeff.	-	-	-	1.868	-	-	-	5.550
(M2 Monetary Aggregate	F-Test Stat.	-	-	-	16.52	-	-	-	9.44
Growth Volatility)	p-value	-	-	-	0.021**	-	-	-	0.223
Junk-AAA Spread	Sum Coeff.	-	-	-	-	0.000	-	-	0.000
(Junk Corporate Bond	F-Test Stat.	-	-	-	-	2.59	-	-	6.02
vs. AAA Bond Spread)	p-value	-	-	-	-	0.920	-	-	0.538
AAA-CP Spread	Sum Coeff.	-	-	-	-	-	-0.001	-	0.003
(AAA Corporate-	F-Test Stat.	-	-	-	-	-	8.93	-	3.96
Prime CP Spread)	p-value	-	-	-	-	-	0.258	-	0.784
Bank Loan Growth Vol	Sum Coeff.	-	-	-	-	-	-	0.404	0.788
(Bank Loan	F-Test Stat.	-	-	-	-	-	-	8.21	6.75
Growth Volatility)	p-value	-	-	-	-	-	-	0.314	0.455
Seasonal Dummies		YES	YES	YES	YES	YES	YES	YES	YES
N. Observations		132	132	132	132	132	132	132	132

Figure 1. Annualized Standard Deviations of US Stock Returns from Monthly Returns in the Year, 1802-2016



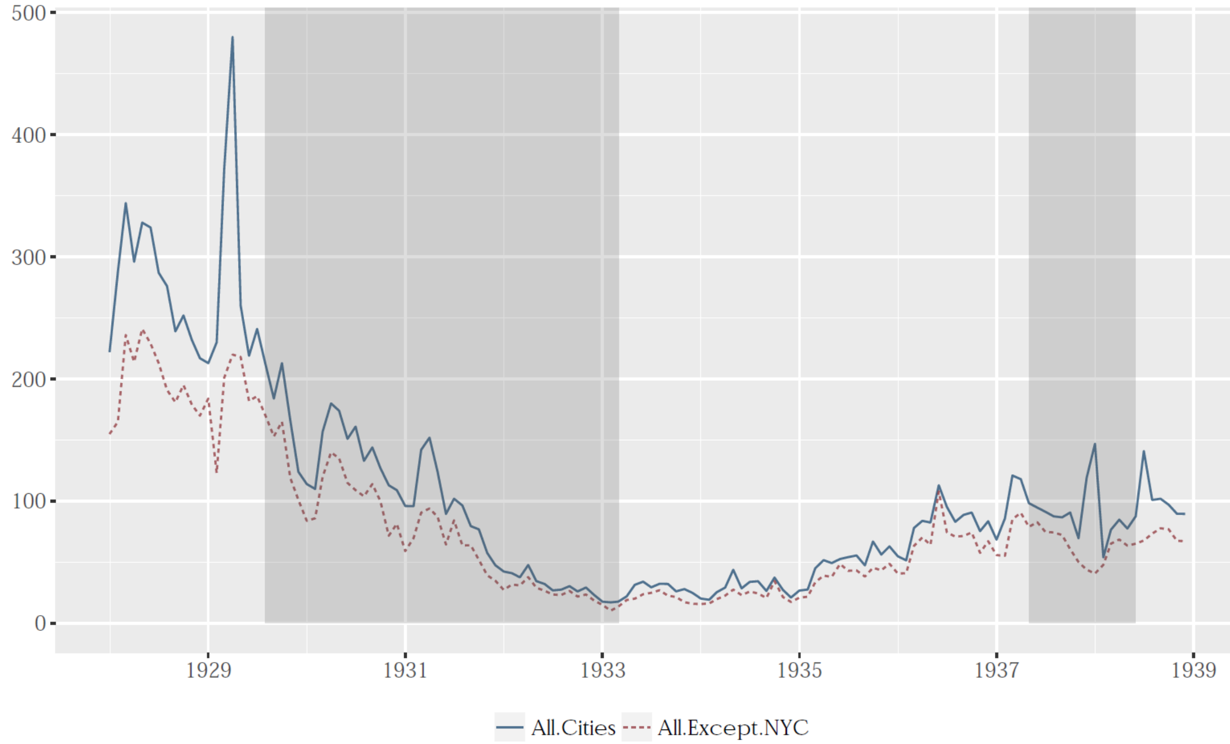
Notes: The figure shows the time series of annualized stock returns volatility calculated from monthly data. The two highlighted periods are the Great Depression of the 1930s and the Great Recession of 2008-2010. The data is the same used in Schwert (1989) and is updated on a regular basis at the website of G. William Schwert. The data and the updated volatility chart is available in http://schwert.ssb.rochester.edu/volatility.htm.

Figure 2. Building Permit Growth Volatility vs. Stock Volatility (1928:M1–1938:M12)



Notes: The larger shaded area is the Great Depression period as defined by the NBER recession dates. The second shaded area is the NBER-defined 1937-38 recession. The data on building permits are taken from various issues of *Dun & Bradstreet's Review*. The stock data are taken from CRSP. Stock volatility is obtained by calculating the monthly standard deviation from daily stock returns. The volatility of the growth rate of building permits is estimated using a standard GARCH(1,1) model as described in the data section.

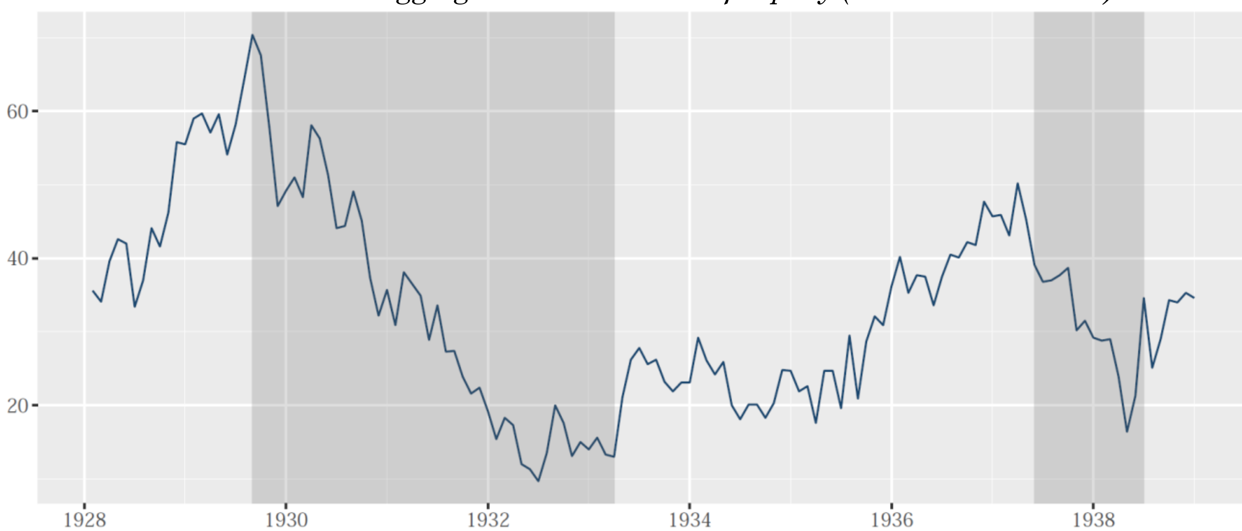
Figure 3. Aggregate Building Permits in the United States: With and Without New York City (1928:M1-1938:M12)



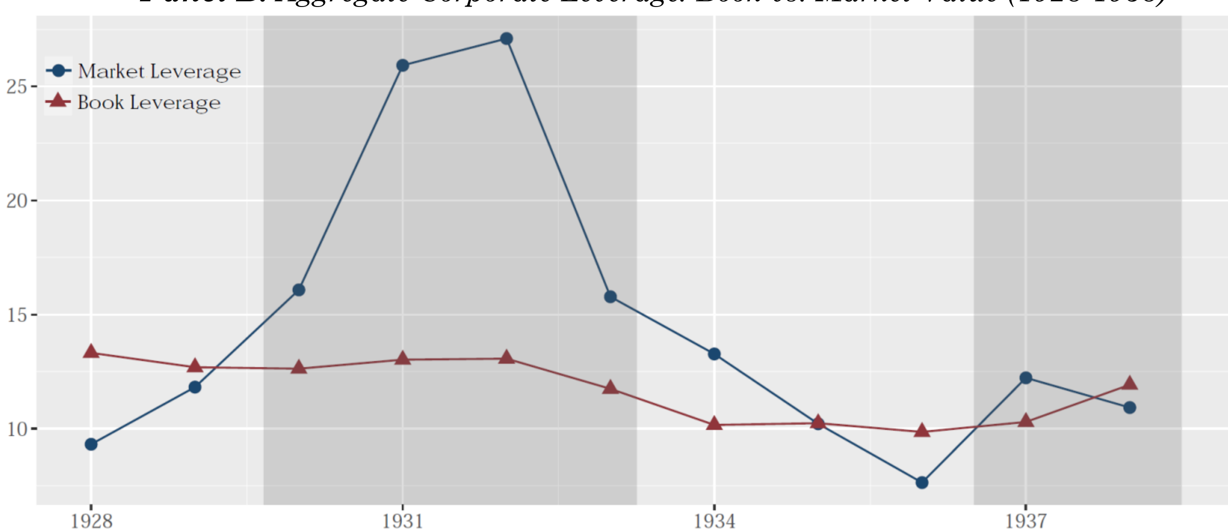
Notes: The first darker shaded area represents the period of the Great Depression as defined by the NBER. The largest spikes registered in the *All Cities* Building Permits time series are in March and April 1929, around six months before the Great Crash of 1929. The data on building permits are taken from various issues of *Dun & Bradstreet's Review*.

Figure 4. Book Measures vs. Market Measures of Aggregate Corporate Leverage (1928-1938)

Panel A. *Aggregate Market Value of Equity (1928M1-1938:M12)*

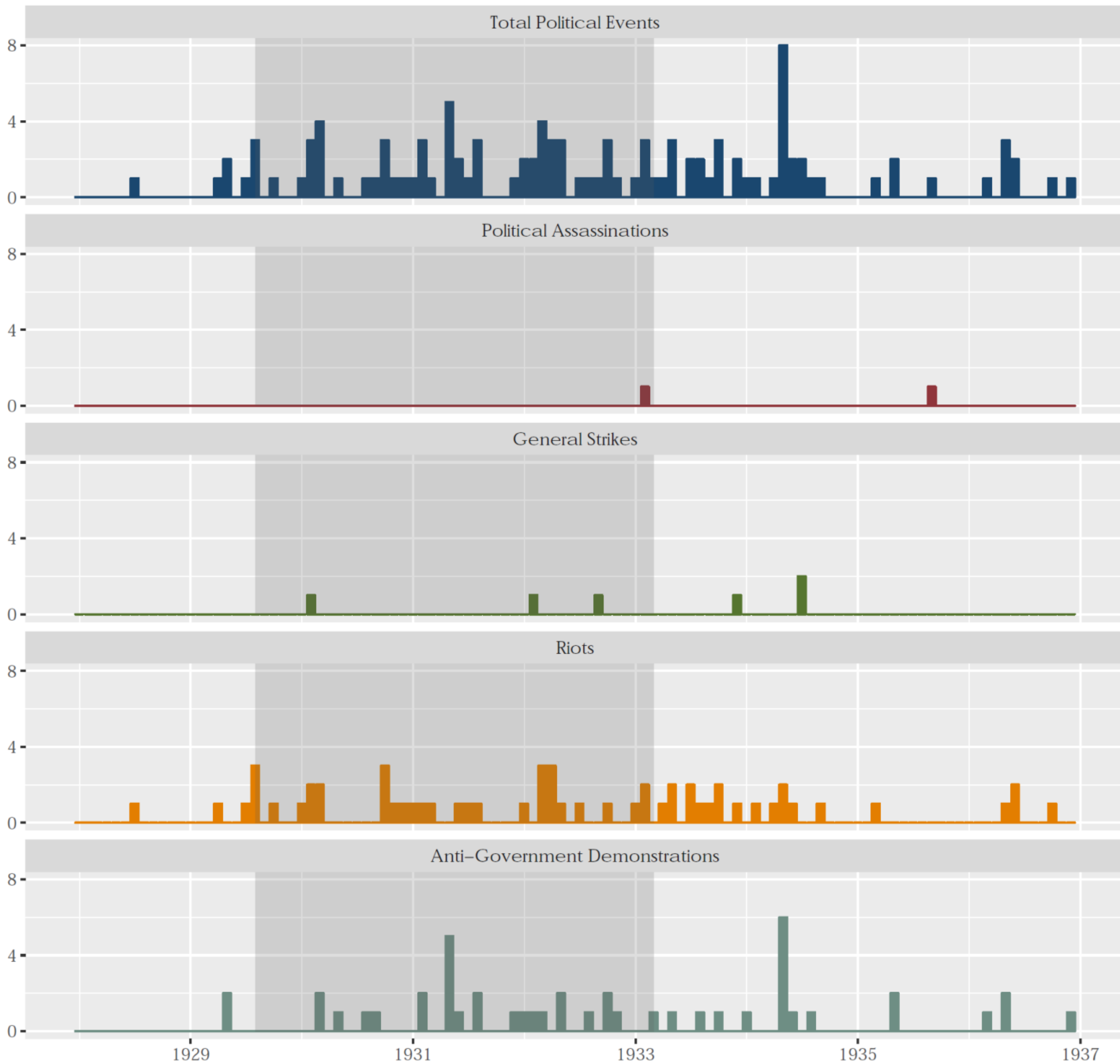


Panel B. *Aggregate Corporate Leverage: Book vs. Market Value (1928-1938)*



Notes: The darker shaded area in both graphs represents the Great Depression as defined by the NBER. In Panel A, the *Aggregate Market Value of Equity* (in Million USD) is the sum of market values for all CRSP Securities, where the market value is calculated as the product of the outstanding number of shares and the price of each security. In Panel B, the *Market Value of Leverage* is defined as *Debt / (Debt + Market Value of Equity)* and the *Book Value of Leverage* is defined as *(Total Debt / Total Assets)*. Both measures of corporate leverage are taken from Graham, Leary, and Roberts (2015).

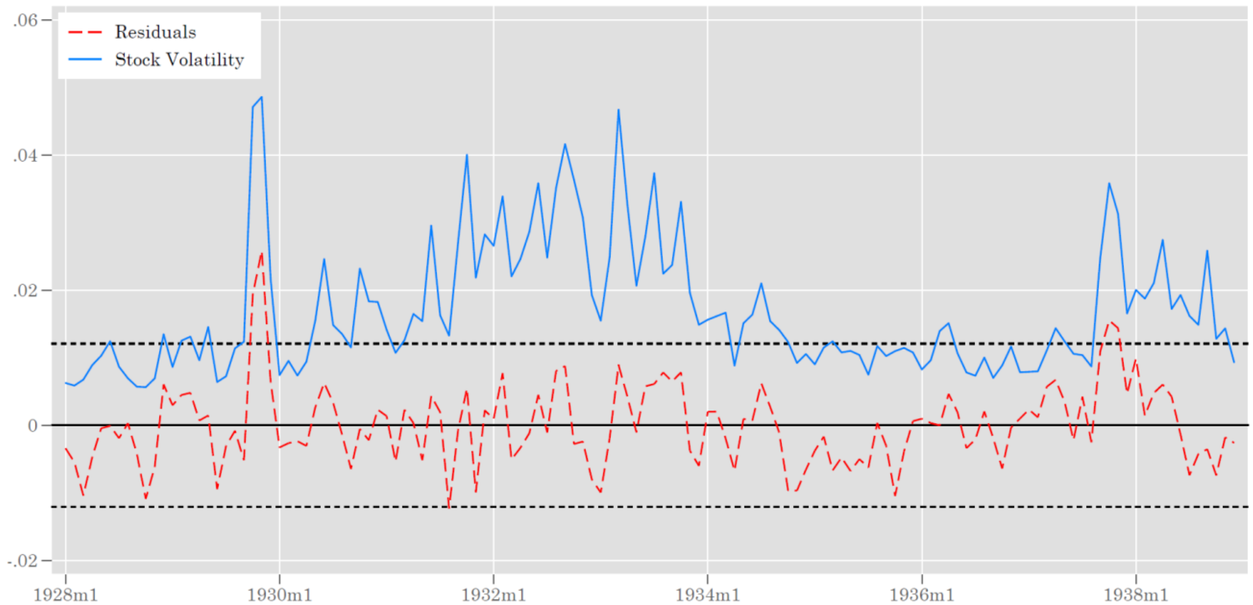
Figure 5. Monthly Frequency of Important Political Events, 1928:M1-1938:M12



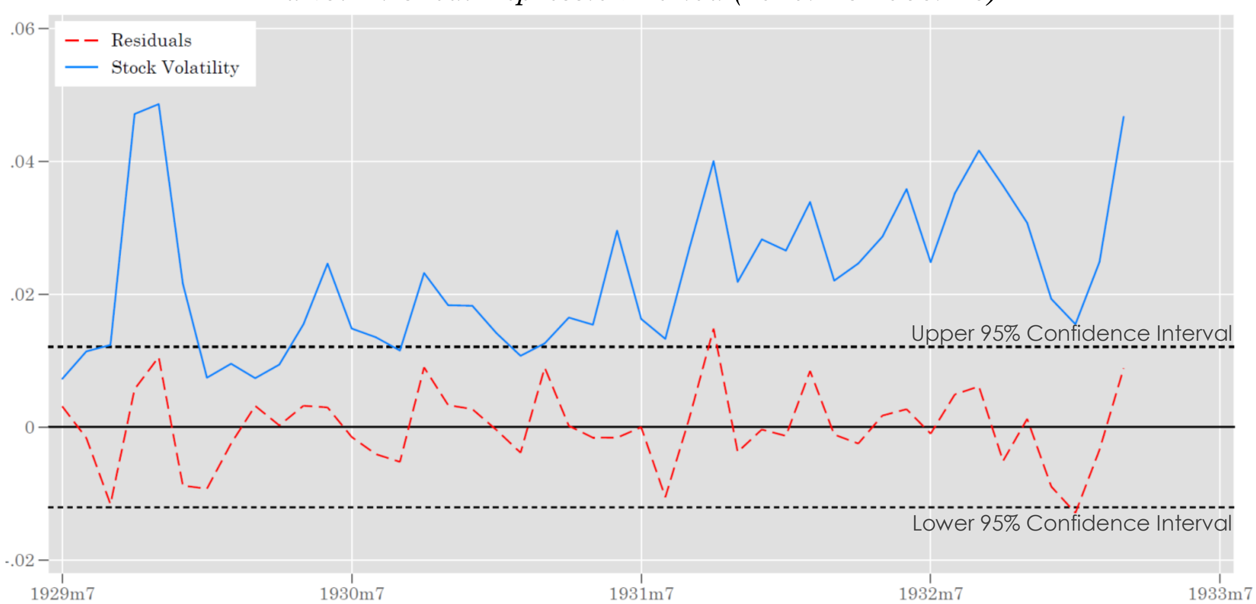
Notes: The shaded areas in all graphs represent recession periods as defined by the NBER. The first darker shaded area is the Great Depression. Data Appendix A.1 describes in detail how each type of event is defined according to Banks' (1976) methodology.

Figure 6. Regression Residuals from Stock Volatility Models

Panel A. *Full Sample (1928:M1-1938:M12)*



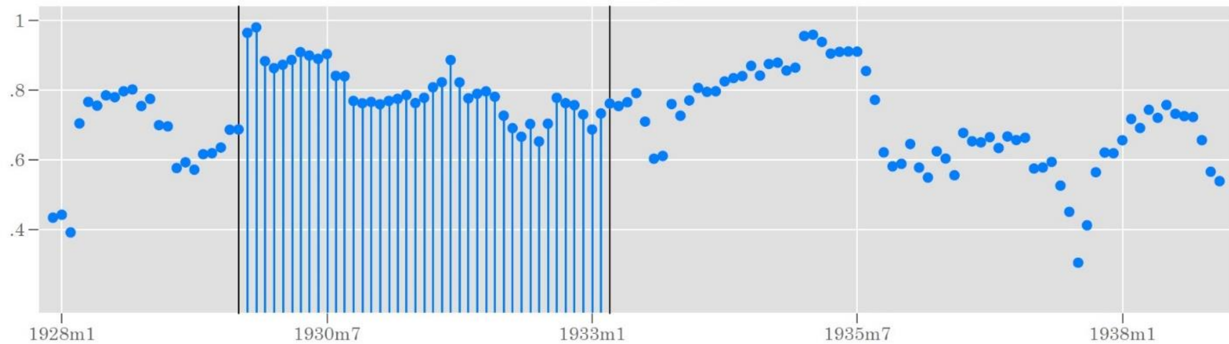
Panel B. *Great Depression Period (1929:M8-1933:M3)*



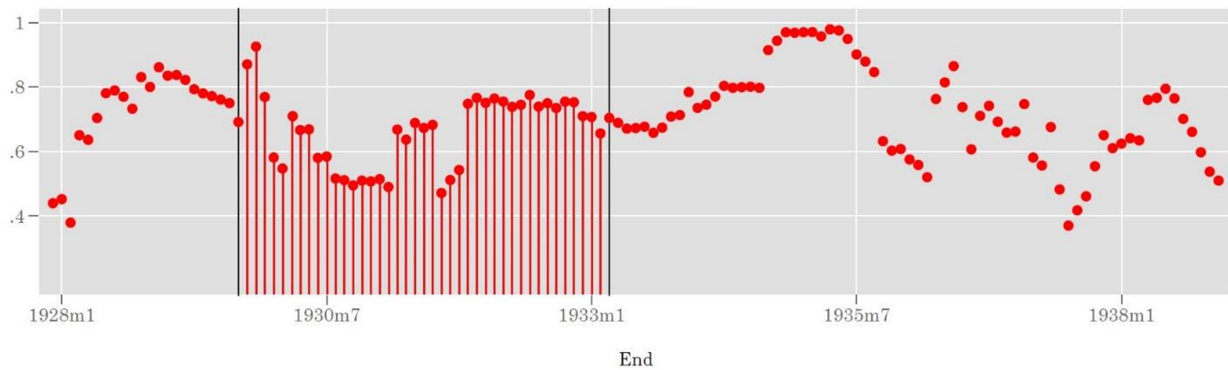
Notes: The figures show the original time series of stock volatility (continuous blue line) and stock volatility regression residuals (dashed red line) after controlling for two variables: financial leverage (*Lev*) and the volatility of the growth rate of building permits (*Permit Vol*). The residuals in **Panel A** are constructed from a regression of stock volatility on financial leverage, the volatility of building permit growth, and a set of seasonal monthly dummies. The residuals shown in **Panel B** are calculated from a regression of stock volatility on financial leverage and the volatility of building permit growth during the Great Depression as defined by the NBER.

Figure 7. R-Squared Value of 24-month Rolling Regressions

Panel A. *All Cities*

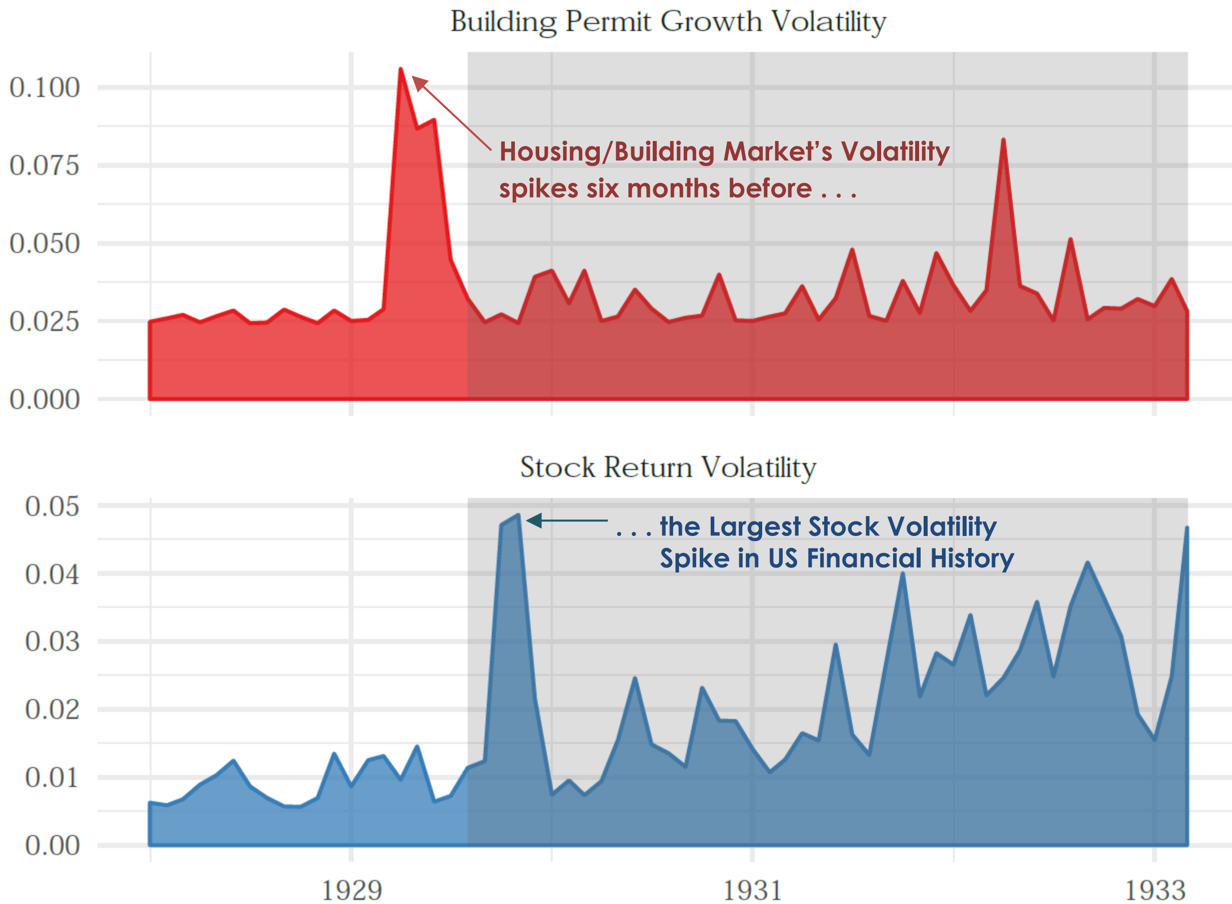


Panel B. *All Cities Except NYC*



Notes: The figures show the R-squared values for rolling 24-month window regressions of Stock Volatility on lags of financial leverage (*Lev*) and volatility of building permit growth (*Permit Vol*). The only difference between panels A and B is that the time series used to calculate *Permit Vol* in **Panel B** subtracts New York City permits from the original 215 aggregate permits series used in **Panel A**. The two vertical black lines indicate NBER recession dates of the Great Depression.

Figure 8. The Volatility of Building Permit Growth Leads Stock Volatility



Notes: The sample period in both figures is from January 1928 to March 1933 to highlight the behavior of both series around the Great Depression (shaded area). The data on building permits are taken from various issues of *Dun & Bradstreet's Review*. The stock data are taken from CRSP. Stock volatility is obtained by calculating the monthly standard deviation from daily stock returns. The volatility of the growth rate of building permits is estimated using a standard GARCH(1,1) model as described in the data section.

Appendix A. Data Sources

A.1. Political Uncertainty Data: Monthly Reconstruction of the Banks (1976) Dataset

We construct a US-monthly version of the classical *Cross-Polity Time-Series* annual dataset originally collected by Banks (1976) for more than 160 countries. The data set is widely used in political science, economics, as well as other social sciences. The *Cross-Polity Times Series* is currently updated every year by Databanks International.[30] We used Banks' (1976) original sources to convert his annual database into a monthly measure for the following types of political events: anti-government demonstrations, assassinations, general strikes, and riots. Specifically, we primarily relied on the search engine for the *New York Times* to pinpoint the monthly date of anti-government demonstrations, assassinations, general strikes and riots.

A.2. Housing Data: US Aggregate and City-Level Building Permits Value

Data are taken from various issues of the *Bradstreet & Dun's Review*. The aggregated series is the sum of city-level data. The index is based on a consistent set of 215 cities for period 1928-1938.

A.3. Stock Exchange Volatility Data

We follow Schwert (1989, 1990a) and calculate stock volatility as the sample standard deviation of the S&P index returns aggregated monthly from daily data.

A.4. Market Value of Corporate Leverage Data

The market value of leverage is taken from Graham, Leary, and Roberts (2015). Their market value of leverage is calculated as (*Debt / Debt + Market Equity*) for non-financial firms. We transform their data from annual to monthly for the period 1920:M1-1938:M12 by linear interpolation.

A.5. Macroeconomic Time Series

All aggregate time series used in our analysis were downloaded from Federal Reserve Bank of St. Louis's (FRED) data base.

[30] The current version of the data is available for purchase at www.cntsdata.com for a larger time and geographic span.