American Economic Review 2008, 98:4, 1370–1396
http://www.aeaweb.org/articles.php?doi=10.1257/aer.98.4.1370

Does Innovation Cause Stock Market Runups? Evidence from the Great Crash

By Tom Nicholas*

This article examines the stock market's changing valuation of corporate patentable assets between 1910 and 1939. It shows that the value of knowledge capital increased significantly during the 1920s compared to the 1910s as investors responded to the quality of technological inventions. Innovation was an important driver of the late 1920s stock market runup, and the Great Crash did not reflect a significant revaluation of knowledge capital relative to physical capital. Although substantial quantities of influential patents were accumulated during the post-crash recovery, high technology firms did not earn significant excess returns over low technology firms for most of the 1930s. (*JEL* G14, N12, N22, O30)

The idea that technological revolutions can explain major swings in stock market value is occupying an increasingly prominent role in the literature on the economics of financial markets. Both the 1990s and the 1920s stock market runups have been linked to the arrival of new technologies and the accumulation of intangible capital by firms (Robert Hall 2001; Bart Hobijn and Boyan Jovanovic 2001; John Laitner and Dmitriy Stolyarov 2003; Ellen McGrattan and Edward Prescott 2004; Lubos Pastor and Pietro Veronesi 2005). No study, however, has analyzed the value of these assets over the life cycle of a stock market boom and bust. This is an important omission, since the performance of the stock market implies that the value of new technology fell away sharply during the crashes of October 1929, and March 2000 (Stephen LeRoy 2004). How important are technologically related assets in driving the stock market upward and in precipitating a crash? How do investors respond to new innovations after the market has initially faltered? This article attempts to answer these questions by looking at the stock market's changing value of corporate patentable assets over the life cycle of the 1929 Great Crash, one of the most important events in American economic and financial history.

According to the dominant view in the literature, rising stock market prices during the 1920s can be explained away by speculation and irrational exuberance. Bradford DeLong and Andrei Shleifer (1991) contend that closed-end funds traded at a significant premium over their fundamental value, while Peter Rappoport and Eugene White (1994) find a sharp increase in the risk premium on brokers' loans that were used to fund equity purchases. DeLong and Shleifer conclude that the 1929 stock market was overvalued by at least 30 percent. The alternative view emphasizes new technology and the intangible assets of firms (Irving Fisher 1930). In this tradition, McGrattan and Prescott (2004) argue that on the eve of the crash the stock market was

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undervalued due to the large proportion of intangible capital in the economy. They back out the value of intangibles from national income statistics using equilibrium relations from a growth model, and estimate that in 1929 the stock of intangible corporate capital was at least 60 percent of the stock of tangible corporate capital. However, innovation and intangibles remain unobserved in these studies. Irving Fisher used anecdotal evidence of new technological developments to support his famous assertion on the eve of the crash that "stock prices have reached what looks like a permanently high plateau." McGrattan and Prescott (2004, 992) concede that, "we do not have direct measures either."

Historical records make these types of assets observable. I track the stock market value of corporate stocks of patentable assets from the 1910s through the 1930s by matching financials for 135 firms compiled from *Moody's Manual of Industrials*, the *Commercial and Financial Chronicle*, and the Center for Research in Security Prices (CRSP), with 65,432 US patents assigned to these firms and 36,772 historical citations that their patents subsequently received. Although patents are an imperfect measure of innovation, and although intangible capital covers a broader set of assets than patented inventions, the measures used here provide important information about how technological change influenced the expected addition to a firm's future free cash flow. Jacob Schmookler (1966, 4–5) argued that when explaining performance differences between nations and firms, the accumulation of intellectual capital is a more significant factor than the accumulation of physical capital. Given effective intellectual property rights institutions at this time, "many of the major American enterprises owed their success to patents" (B. Zorina Khan 2005, 298). The problem of heterogenous patent quality is overcome using historical citation counts—how many times a patent assigned to a firm in the sample between 1910 and 1939 is cited in patents granted between 1975 and 2006.[1] Despite the long lag between the sample patents and the 1975–2006 patents that cited them, I argue that historical citation counts can be used with a similar degree of confidence to modern citations that are habitually used as a measure of the technological significance of an invention (Bronwyn Hall, Adam Jaffe, and Manuel Trajtenberg 2005).

I combine the patent and financial data in two ways to measure the changing stock market value of patentable assets. First, the market value of a firm is assumed to be the sum of its physical and technological knowledge capital in a conventional q-theory setting, as used by Zvi Griliches (1990). I run q regressions for the 1910s and 1920s to estimate changes in the market value of patent capital between these decades. In a second approach, I examine the changing market value of patentable assets during shorter event windows around the Great Crash. Whereas the q regressions rely on end-of-year balance sheet data, I match monthly return data from CRSP with monthly patent data on the firms in the sample to run excess return regressions. I provide parameter estimates of the excess returns to patent capital over four phases of the 1920s and 1930s stock market—pre-runup, runup, crash, and post-crash.

The q regressions strongly support the view that the 1920s stock market runup was largely driven by the changing valuation of corporate knowledge assets, given their high weight in the market relative to overall firm assets. They show that the market value of patent capital was significantly higher during the 1920s compared to the 1910s. In particular, I find a significantly positive effect of historically cited inventions on q for the 1920s, indicating that market prices were responding to signals about the quality of technological inventions.

I also find a strong economically and statistically significant effect of historically cited patents on excess returns during the late 1920s stock market runup. Furthermore, the results show that the Great Crash did not represent a large revaluation of knowledge assets relative to physical

[1] The first front-page citations date from 1947, but only citations from 1975 are available in a systematic form.

capital. Unlike the 1920s, the pricing of innovation does not explain market dynamics for the Depression years. During the post-crash phase, corporations continued to invest heavily in new technology and accumulated important patents. Patent capital did not, however, earn significant excess returns for most of the 1930s.

The remainder of the article is organized as follows. In the next section I provide a brief survey of the period, and a historical context within which these stock market changes occurred. Section II describes the matched dataset of company financials, patents, and historical citations, Section III outlines the empirical specifications of the Tobin's q and monthly excess return regressions, Section IV presents the results, and Section V concludes.

I. Historical Background

The early twentieth century was an important period when technological innovation became an uncertain component of a firm's stock market value. This epoch, while not altogether exceptional given previous technological revolutions (Carlota Perez 2002), was distinguished by a particularly broad base of innovations that became the principle object of stock market speculation (Fisher 1930). Fundamentals of the railroad economy, which preceded this era, had been much easier to value, and although this industry was not immune from runups and crashes (Margaret G. Myers 1970, 126–28; Pastor and Veronesi 2005), it had done little to prepare investors for assessing the new technologies to come. Innovation was central to economic growth during the rise of the corporate economy as firms built on the scientific advances of the Second Industrial Revolution (Alfred Chandler 1990; Joel Mokyr 2002, 105–16). The formation of in-house industrial research laboratories acted as an institutional conduit for links between academic science and the commercialization of industrial innovation (Mowery 1990; Megan MacGarvie and Jeffrey Furman 2005).

The 1920s, in particular, was a period of unprecedented technological advance and intangible capital growth. There were good reasons why Joseph Schumpeter (1939, 753) labelled this decade the "Industrial Revolution of the Twenties." The *National Research Council*'s survey of innovation in the American economy reported a more than threefold increase in the number of corporate industrial research labs from 521 in 1921 to 1,620 in 1931. Between 1921 and 1927 the number of scientists and engineers employed in industrial research laboratories more than doubled from 2,775 to 6,274 (David Mowery and Nathan Rosenberg 1998, 21-22). Electricity surpassed steam as a source of power during this decade, which boosted manufacturing productivity (Paul David 1990). Hermann Staudinger's early 1920s discoveries in macromolecular chemistry revolutionized product development in a range of industries, and especially at DuPont where 1920s R&D led to the introduction of nylon and neoprene (David Hounshell and John Kenly Smith Jr. 1988; Mokyr 2002, 109). A wave of new and improved products generated by the application of science reached consumers down to the level of individual households. In 1921, 5,000 mechanical refrigerators were sold in the United States, rising to 906,000 a decade later (H. Laurence Miller 1960, 197). Virtually no household had a radio in 1920, compared with 12 million households in 1930 (David Strömberg 2004, 191).

Given the diffusion of the radio and the profitability of this sector, nothing was more incongruous than the collapse of the exemplar high technology stock of the 1920s–Radio Corporation of America (RCA). Robert Sobel (1986, 90) writes that on the eve of the crash, "RCA's outlook had never been brighter." Harold Bierman (1998) notes more generally that in late 1929 there were no noticeable signs in the press that a crash in the market was imminent. Yet the crash was set in motion on October 24, 1929 (Black Thursday), when the Dow Jones closed at 299.5, down almost 100 points from its September 1929 high, as a record of just under 13 million shares were traded.[2] A short rally in the market over the following days was reversed as sell-off orders came in on Black Monday of October 28. Black Tuesday of October 29 was one of the worst days on the US stock market with the Dow ending at 230.1. The next day, *The New York Times* noted that "240 Issues Lose $15,894,878,894 in a Month," illustrating the precipitous decline in market capitalization that had taken place (Bierman 1998, 67).

Despite a weak recovery from the crash and the Great Depression, many firms continued to push out the frontier of technological development during these years. Mowery and Rosenberg (1989, 6–7) report a twofold increase in real research and development expenditures during the 1930s. According to Michael Bernstein (1987), the impact of the depression was highly uneven. Sectoral transformation meant that some industries such as textiles were hit particularly hard, but others like chemicals continued to be technologically dynamic. Even within industries, the impact of the Great Depression varied. Timothy Bresnahan and Daniel Raff (1991) find significant heterogeneity in the experience of firms in the motor vehicles industry, with low-average-cost firms being more likely to survive the Depression-era shakeout. For some firms, the recovery from the 1932 slump was swift. RCA, the high technology stock of the 1920s that was bludgeoned by the crash, returned to profitability in 1934 (Sobel 1986, 107–08).

II. Data

To explore the relationship between technological change and the stock market, I use a dataset on the technological and financial characteristics of American publicly traded corporations. I use historical balance sheets as documented in *Moody's Manual of Industrials*, and share price data from the *Commercial and Financial Chronicle* and CRSP, and I merge these data with information on the patents assigned to individual companies using records from the United States Patent and Trademark Office (USPTO).

A. *Balance Sheets and Equity Prices*

Moody's published the annual financial statements of firms in its *Manual of Industrials*, which is a standard source for historical company financial data. Before the formation of the Securities and Exchange Commission (SEC) in 1934, financial reporting was neither mandatory nor regulated, and so the discretion of management dictated the accuracy of the accounting data supplied. On the upside, the 1920s witnessed an increase in the transparency of financial reporting, which gave rise to broader efforts to improve financial disclosure for listed companies. The scrutiny of the press and the independent auditing of financial accounts by companies such as Price Waterhouse and Ernst & Ernst alleviated the problem created by asymmetric information. By the mid-1920s approximately 90 percent of the companies traded on the New York Stock Exchange (NYSE) had voluntary audits in place (May 1926, 322).

The balance sheets of firms contained in *Moody's Manual of Industrials* provide a useful window to the process of innovation at this time. Prior to the standardization of financial reporting by the SEC, intangibles such as patents and trademarks were often capitalized by firms in their annual disclosures, albeit at a sometimes overinflated rate (Kirsten Ely and Gregory Waymire 1999). General Motors estimated that it possessed $20.3 million of intangibles in 1920 and $50.7 million of intangibles in 1929, equivalent to around 8 percent of its physical capital stock. American Bosch Magneto Corporation, which manufactured devices for internal combustion engines, valued patents alone at between $594,176 and $633,356 from 1924 to 1929, equivalent

[2] The Dow Jones had peaked on September 3, 1929, at 381.2.

to around one-third of the total assets of the company. Gillette Safety Razor valued patents at an average of 50 percent of tangible capital between 1920 and 1929. RCA valued intangibles at over 100 percent of the physical assets on its balance sheet. The company also deemed patents and licensing to be so important that it devoted a separate section to them in its annual reports that were published in the *Commercial and Financial Chronicle*.[3]

In order to estimate q and excess return regressions, I collected balance sheet data from the volumes of Moody's on every firm with at least four years of continuous records starting in 1929 and moving backward in time to 1910. Four years of data gave a reasonable span over the time series dimension, so I was able to cross-check the financial statements for unusual entries. I also tracked the firms that were in the sample in 1929 through to the end of 1939 to analyze the changing stock market value of patentable assets after the Great Crash. I matched the end-of-year balance sheet data with end-of-year share price data from the *Commercial and Financial Chronicle*, which I supplemented with share price data from CRSP from December 1925 to December 1939. For the excess return regressions, I also collected the 30-day Treasury bill rate from Ibbotson Associates to calculate the excess of the value-weighted monthly return given in CRSP over the risk free rate.

The final dataset consists of 135 firms, which covers approximately a quarter of all publicly traded industrial and manufacturing firms at the time. To explore potential biases in the distribution of the firms on which data were available, Figures 1A and 1B compare data from Moody's with Alfred Chandler's list of the 200 largest enterprises in *Scale and Scope* and the population of NYSE firms listed by CRSP. Figure 1A reflects the fact that while the sample includes the large Chandlerian corporations such as General Electric, DuPont, and US Steel, it also includes firms with smaller-sized assets. Figure 1B shows that by market value the sample of firms is more closely aligned with the broader set of listed companies, although smaller companies, which made up a significant proportion of the stock market, are somewhat underrepresented.[4] Figure 1C shows a slight bias in the data, given that the firms in the sample underperformed the S&P Composite Index during the runup and the crash, but outperformed it during the post-crash period of the 1930s.[5]

The raw financial data from Moody's can be used directly as inputs in monthly excess return regressions to create standard control variables such as the market value of common stock (a proxy for size) and the ratio of book-to-market value; they require additional computations to calculate Tobin's q. For this purpose I followed the procedure of Eric Lindenberg and Stephen Ross (1981). Market value was calculated as the number of shares outstanding, multiplied by the year-end price, plus the value of preferred stock, plus the book value of debt.[6] The replacement cost of capital assets, K, was calculated using the following recursive formula:

[3] For example, in a March 23, 1929, report, the company noted that "the most important technical advance of the year was the successful application of the alternating current radiotron to the superheterodyne circuit." The superheterodyne receiver is the type of receiver most radios use even today. It allows a radio to work better by preventing needle drift and interference from other channels.

[4] The median total asset value of the firms in the sample in 1929 is \$57.1m, which compares with a median of \$79.8m for Chandler's 200 largest firms in 1930. The median market value of the common stock of the firms sampled is \$38.9m compared with \$27.5m for the firms in CRSP.

[5] The small differences illustrated might be driven by the mix of railroad, industrial, and utility sectors in the S&P, compared to the industrial concentration of the sample. Eugene White (1990) notes that the performance of these sectors did vary over the period.

[6] I calculated the market value of preferred stock as a perpetuity by dividing preferred dividends by Moody's (1929, xix) average yield on preferred stock. Given the lack of data on the timing of bonded debt to fully replicate the Lindenberg and Ross computations, I assumed that market value of debt equalled its book value.

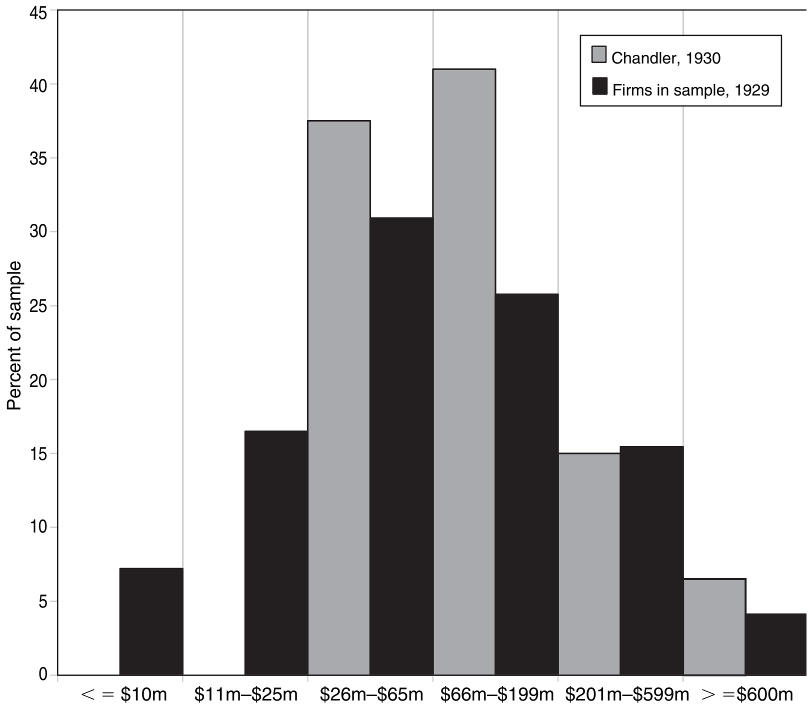

Figure 1A. Benchmarking Total Assets against Chandler's 200 Largest Corporations

Notes: Data on total assets for Chandlerian firms from Chandler (1990, app. A.2, 644–50). For the firms in the sample, total assets are from the balance sheets given in Moody's.

$$K_{it}^{rc} = K_{it-1}^{rc}\left[\frac{1+\lambda}{1+\rho}\right] + (K_{it}^{bv} - K_{it-1}^{bv}), \tag{1}$$

where the superscripts denote replacement cost (rc) and book value (bv), respectively, λ is the inflation rate, and ρ is the depreciation rate.[7] To calculate the replacement costs of inventories, I multiplied the book value of inventories at time t by the ratio of the wholesale price index at time t to time $t-1$.[8] Tobin's average q was then computed as the market value of the firm divided by the replacement cost of capital assets and inventory.

Figure 2 provides a long-run perspective on the data by plotting Tobin's q for the firms in the sample against the series of Olivier Blanchard, Changyong Rhee, and Lawrence Summers (1993, BRS), the series of Laitner and Stolyarov (2003), and the adjusted series of Stephen Wright (2005).[9] A comparison of the current series with BRS, which is aligned with Wright's revised estimates, suggests some bias in the data toward successful firms with higher values of q, although the underlying trend in each data series is similar. Figure 2 shows that Tobin's q was well below its equilibrium value of unity during the 1910s but rose above one during the 1920s

[7] For the inflation rate, I use the GNP implicit deflator from *Historical Statistics of the United States*, F 1-5. I set the depreciation rate at 5 percent in accordance with Lindenberg and Ross (1981, LS).

[8] The wholesale price index is from *Historical Statistics of the United States*, E 40.

[9] Wright (2005) argues that LS overestimate the numerator and understate the denominator of q, which accounts for the difference between their respective estimates shown in Figure 2.

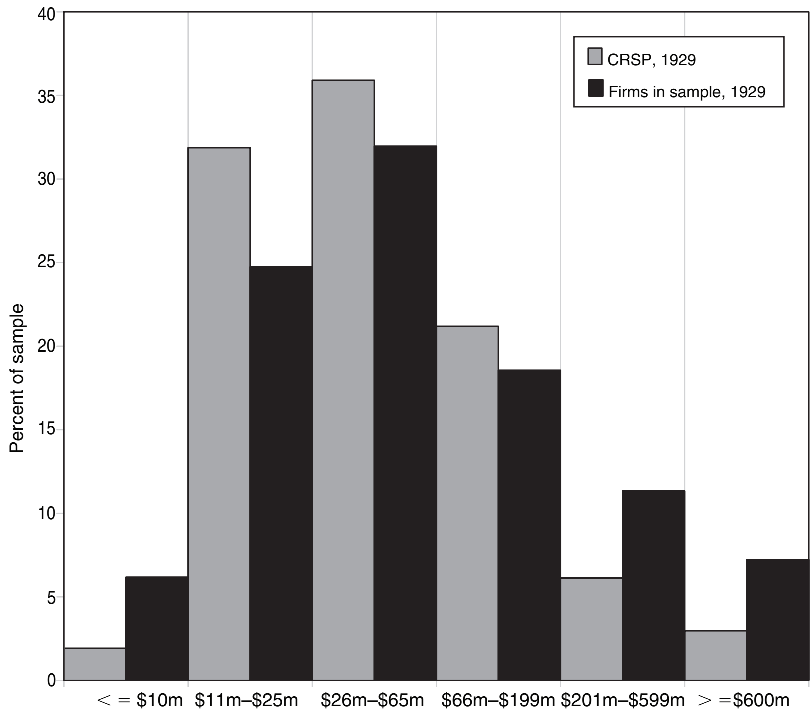

Figure 1B. Benchmarking Market Value against the Population of CRSP Firms

Note: Market value of common stock is year-end number of shares outstanding multiplied by year-end share price.

stock market runup. This basic pattern closely resembles that of the late twentieth century where Hall (2001), Hobijn and Jovanovic (2001), and Laitner and Stolyarov (2003) have documented a drop, followed by a rise, in stock market capitalization during the evolution of the information and communications technology revolution.

B. *Patents*

To complement the financial data, I obtained counts of all US patents that were assigned to each firm in the sample between 1910 and 1939. In accordance with US patent law, patents were granted to individuals (the true and first inventor) and subsequently assigned to firms if the inventor chose to transfer intellectual property rights. The bulk of these assignments would have come from the employees of companies, although some would have been arms-length transactions conducted in the market (Naomi Lamoreaux and Kenneth Sokoloff 2005). For the period 1920 to 1939, I collected 51,832 assigned US patents using automated downloads from the search engine of the European Patent Office. Additionally, for the period 1910–1919, I hand entered 12,602 assigned patents from volumes of the *Official Gazette* of the USPTO.[10]

[10] This involved a two-step process. First, I obtained from the *Official Gazette* lists of names of inventors who assigned their patents to particular companies. Second, I looked up the individual names themselves to obtain the patent counts.

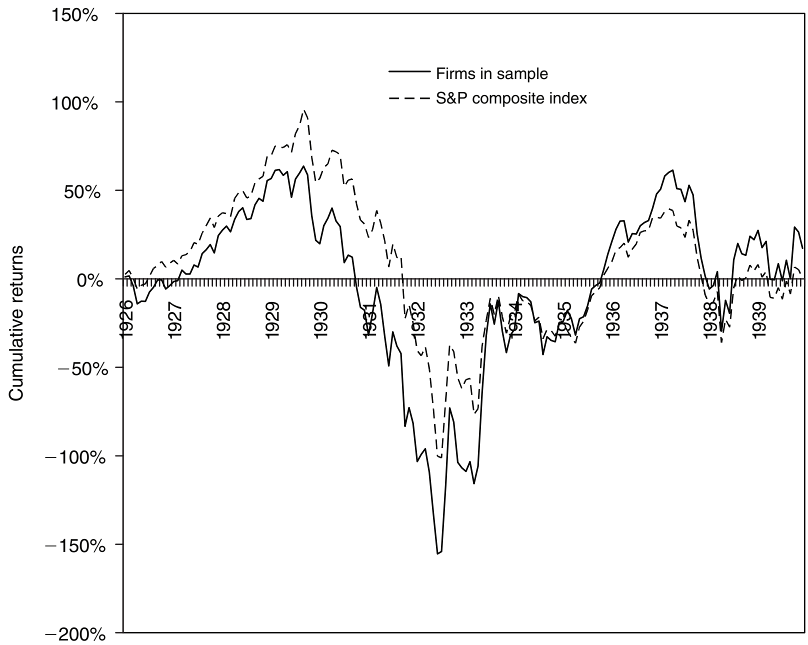

Figure 1C. Benchmarking Cumulative Returns Using the S&P Composite Index

Notes: Cumulative returns for firms in the sample and for the S&P are calculated from CRSP for the time period January 1926 to December 1939.

The distribution of patents assigned to the firms is highly skewed. There are few high-frequency patenting companies in the sample, such as General Electric and Westinghouse, which were assigned between 400 and 500 patents per year. The median patenting firm was assigned 20 patents per year during the 1910s, 27 patents per year during 1920s, and 67 patents per year during the 1930s.[11] Khan (2005) documents the significance of patenting during this period as US corporations used patents widely to protect their intellectual property rights. Fisher (1930, 127) noted how output from inventive effort startled Commissioner of Patents Thomas E. Robertson, who wrote in his 1929 report that "it is noteworthy that more patents have been granted during the last ten years than during the 100 years from President Washington's inauguration in 1789 until President Harrison's inauguration in 1889."

A particularly important feature of Figure 3 is that firms accumulated increasing stocks of patentable assets despite the Great Depression. This provides an opportunity to examine the extent to which knowledge capital explains stock market dynamics after the 1929 crash. Figure 3 fits in with the idea that such major sectors of the economy as electrical equipment manufacturing were active in technical change during the 1930s (Bernstein 1987). General Electric, for example, was granted 6,414 US patents during the depression years, almost twice as many as it had been granted during the 1920s. Although unemployment reached new highs in 1932, the recruitment of scientists and engineers to work inside firms continued at an accelerating rate between 1933 and 1940 (Mowery and Rosenberg 2000, 814). These changes had significant effects on productivity.

[11] Twenty-eight firms in the sample did not patent at all.

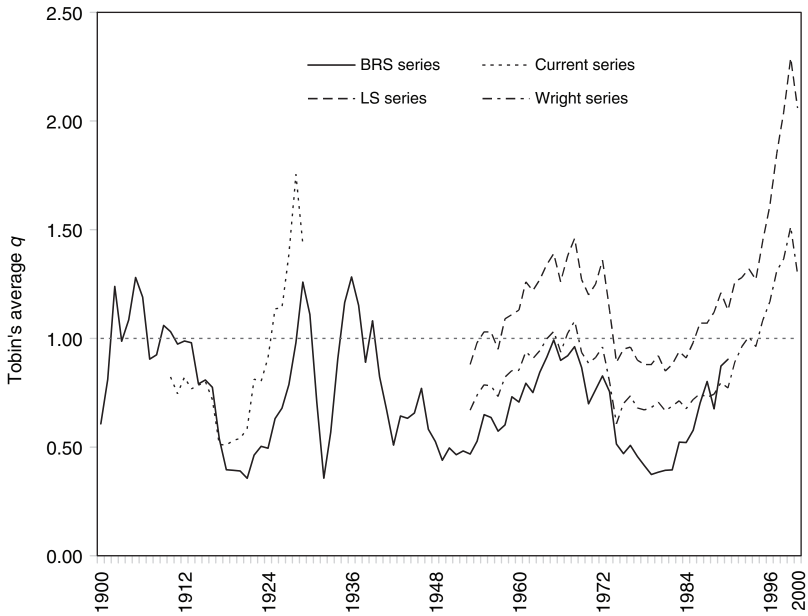

Figure 2. Tobin's q over the Long Run

Note: BRS series from Blanchard, Rhee, and Summers (1993); LS series from Laitner and Stolyarov (2003); Wright series from Wright (2005, Table A1, column 7).

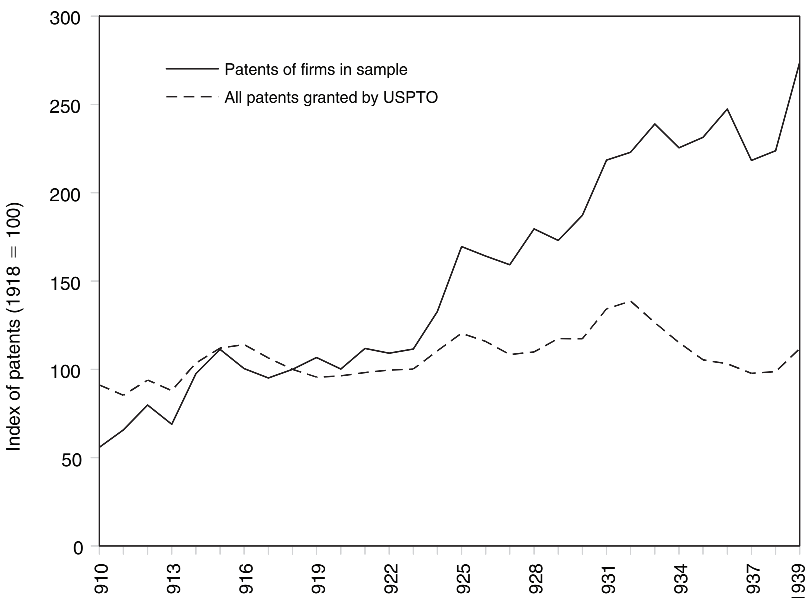

Figure 3. Indexes of Firm Patents and Total USPTO Patents, 1910–1939

Note: USPTO series from annual reports of the *Official Gazette*.

According to Alexander Field's (2003) estimates, both technological development and organizational improvements explain most of the multifactor productivity advance of the era.

C. *Historical Patent Citations*

Effective intellectual property rights created incentives for firms to invest heavily in R&D and patents. Patent counts alone, however, provide a useful but narrow measure of technologically related changes.[12] Although studies have shown broadly consistent results in market value equations using patents and independent measures of innovation (Paul Geroski and Christopher Walters 1995; Richard Blundell, Rachel Griffith, and John Van Reenen 1999), the literature is unanimous in its verdict that raw patent counts need to be quality adjusted before they can convey accurate information about the process of technological development (Hall, Jaffe, and Trajtenberg 2005).

The problem of variation in patent quality is particularly acute during the early twentieth century. Corporations used patents as an alternative to mergers during this period to protect their market share. Mowery (1990, 346) argues that "firms threatened by prosecution under the 1890 Sherman Act used industrial research to diversify out of their primary industry, and to accumulate patents that could sustain or protect a dominant market position." Josh Lerner, Jean Tirole, and Marcin Strojwas (2007) describe how firms used patent pools to maintain cartels because they circumvented antitrust laws. General Electric was well known for its "defensive" patents in the electrical lamp market (Leonard C. Reich 1977), while the leading players in the chemicals industry, especially DuPont, used strategic patenting to deter entry (Hounshell and Smith 1988). Firms often maintained intellectual property rights regardless of the intrinsic value of the invention.

To address this problem I use historical patent citations as a measure of a patent's technological importance. The intuition behind the historical citations measure follows Trajtenberg's (1990, 174) assertion that "if citations keep coming it must be that the innovation originating in the cited patent had indeed proven to be valuable." Although most citations to patents occur within a decade of their own grant date (Ricardo Caballero and Jaffe 1993), in many cases the citations are historical in nature. Because novelty is a condition of patentability, the patenting process requires inventors to make reference to all prior art relating to an invention, regardless of how far back in time it might go. Citations are searchable in a systematic form either from 1976 to the present using the USPTO's full-text database or from 1975 to 1999 using the NBER data file.[13]

Using the second of these sources, Figure 4 illustrates that large shares of historical patents are cited in patents granted by the USPTO between 1975 and 1999. Historical citations come at a faster rate beginning with the path-breaking inventions associated with the Second Industrial Revolution in the last quarter of the nineteenth century (Mokyr 1990, 113–48). If, as is commonly assumed, only a small percentage of patents develop into economically feasible innovations, it is extraordinary that so many historical patents continue to be cited so long after their initial grant date. Table 1 shows that, on average, 14.7 percent of the patents assigned to firms in the sample during the 1910s are subsequently cited between 1975 and 1999, rising to 20.7 percent in the 1920s and 29.3 percent in the 1930s.[14] A comparison of the citations received by 1999 in

[12] There are also other limitations of patent data, in particular that many inventions are not patented, and that the protection disclosure trade-off varies across industries (Wesley Cohen, Richard Nelson, and John Walsh 2000; Petra Moser 2005).

[13] Citations to prior art have been included in USPTO patent specifications since 1947, before which references to prior art were disclosed only in the unpublished "file wrapper" of patent records.

[14] The proportion of patents receiving more than one citation during these decades is 58.7 percent, 65.4 percent, and 74.4 percent. The most highly cited patent in each decade is: Locke H. Burnham's *Transformer*, assigned to General

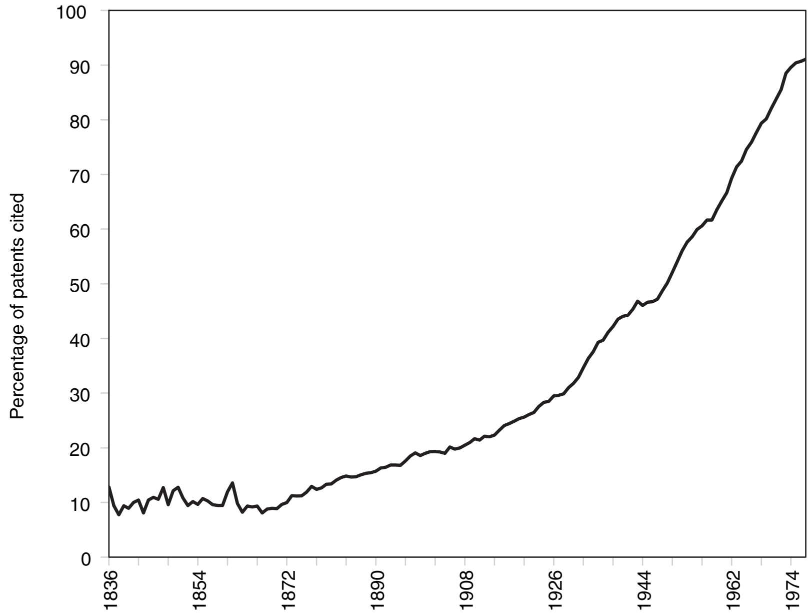

Figure 4. Percentage of Historical Patents Cited in the NBER Data File

Note: Percentage of patents cited is share of patents granted by the USPTO in each year from 1836 to 1974 that are cited at least once by patents granted between 1975 and 1999.

the NBER data with those received by 2006 suggests that the life cycle of these historical citations is not yet complete.

What is the economic significance of patent citations with such long lags? Like patents and patent examiners, not all citations are equal. Iain Cockburn, Samuel Kortum, and Scott Stern (2002) find that patent examiner heterogeneity strongly influences citation patterns, and therefore some of the citations observed in the current sample will be an artifact of the examination system. Patent examiners, along with the patent applicant and attorney, search through past patents granted to identify earlier disclosures of the technology, and with this mix of influences it is impossible to tell what the inventor knew at the time of the invention. To get some insight into this aspect of the data, I looked at citations made to the patents of firms in the sample after the 2001 reporting change that allows examiner-added citations to be identified. Where examiners add citations, it is less likely that the inventor benefited from a knowledge spillover. Juan Alcácer and Michelle Gittelman (2006) report that on the average patent between January 2001 and August 2003, 63 percent of citations are added by examiners. Table 1 shows much lower shares of examiner-added cites at 43 percent, 45 percent, and 42 percent for my 1910s, 1920s, and 1930s samples, respectively.[15]

Electric in 1919 (30 citations); Robert R. Williamson's *Dynamo Electric Machine*, assigned to Allis-Chalmers in 1922 (33 citations); and Clarence Hansel's *Recording Device*, assigned to RCA in 1933 (103 citations). See, respectively, patent numbers 1,304,451, 1,418,856, and 1,941,001. The average citation lag falls systematically from 71 years to 51 years between the three decades.

[15] This finding is consistent with Alcácer and Gittelman's regression showing that older patents are more likely to be associated with inventor-added rather than examiner-added citations.

Table 1—Patent Descriptive Statistics

	1910s	1920s	1930s
Number of patents	12,602	20,072	32,778
Number of citations, 1976–2006	3,741	8,904	24,127
Examiner added citations	43%	45%	42%
Percent of all patents cited	15.89%	22.10%	30.73%
Mean citations of cited patents	1.87	2.01	2.39
	[1.99]	[2.09]	[2.93]
Number of citations 1975–1999 (NBER)	3,010	7,417	20,302
Self-citations	113	307	840
Percent of all patents cited	14.67%	20.71%	29.32%
Mean citations of cited patents	1.83	1.78	2.11
	[1.95]	[1.53]	[2.08]
Mean citation lag (years)	70.9	61.13	50.76
	[7.56]	[7.70]	[7.85]

Notes: Standard deviations in brackets. Citations for 2006 were collected as of end of February 2006. Statistics for examiner-added citations are based on random samples of 100 patents in each of the decades and refer to citations added by examiners as identified after the 2001 reporting changes. Self-citations are removed through patent assignee matches.

Case examples from the data support the hypothesis that long-lagged citations are a valuable source for identifying knowledge flows stemming from historical innovation. A 1927 patent granted to Samuel Sheppard, a star scientist at Eastman Kodak, relating to a sensitizer for photographic emulsion is widely cited in the industry.[16] Wallace Carothers's 1937 patent for synthetic fiber, assigned to DuPont, which is one of the most important innovations of the twentieth century, is cited 57 times between 1976 and 2006.[17] Given the wide distribution of citations over firms and industries, it is unlikely that any significant bias is introduced by a propensity to cite "classic" patents.[18] Historical citations may be a better measure of the ultimate success of an invention because they capture innovations that are particularly influential and long-lived.

III. Empirical Specifications

Historical citations data are particularly useful for analyzing the changing market value of patentable assets, because they provide an opportunity to examine whether investors were sufficiently sophisticated to respond to the quality of technological inventions. The citations data provide a retrospective measure of inventions that turned out to be important, and so are orthogonal to the information available to investors at the time. I use two approaches to examine whether patents and historical citations can be correlated with changes in the stock market. The first approach uses the method pioneered by Griliches (1981) by relating Tobin's q (the ratio of market value to capital at replacement value) to the patentable assets held by firms for the 1910s and 1920s. The second approach uses the patent data in monthly excess return regressions to examine the stock market's changing value of patentable assets over shorter event windows around the 1929 Great Crash.

[16] See patent number 1,574,944. The origins of silver halide photography go back at least to John Schulze, a German physicist, who in 1727 noticed that certain silver salts darkened when exposed to light. Samuel Sheppard discovered that organic sulphur in gelatine-based emulsions significantly increased its light sensitivity.

[17] See patent number 2,130,948.

[18] There are many less famous examples of historical technological dependence. Kenneth Loose of the Loose-Wiles Biscuit Company was granted several highly cited patents for crackers and shredded wheat in an industry not noted for patent protection. See, for example, patent numbers 1,975,326 and 2,013,003. The food industry is more typically associated with secrecy as a way of protecting intellectual property rights.

A. *Tobin's q Regressions*

The model proposed by Griliches (1981) is the standard method for estimating the role of patents and R&D assets in affecting stock market valuations. The model posits a value function where the market value of the firm, V, is equal to the sum of its physical assets, K, and applied knowledge assets G:

$$V_{it} = (\pi_t K_{it} + \eta_t G_{it})^{\psi}, \tag{2}$$

where π and η are the shadow price of capital and applied knowledge assets, respectively, and it is assumed that constant returns to scale hold such that $\psi = 1$. The mechanics of this model, which are described more fully in Hall, Jaffe, and Trajtenberg (2005), imply an estimating equation of the form:

$$\log q_{it} \equiv \log(V/K)_{it} = \log(1 + \phi_t G_{it}/K_{it}) + \varepsilon_{it}, \tag{3}$$

where ϕ_t measures the shadow value of applied knowledge assets relative to the physical assets of the firm, and the approximation $\log(1 + x) \simeq x$ is often used to yield a semi-logarithmic equation. Deviations from the equilibrium condition $(q = 1)$ arise because firms possess assets that are unaccounted for in the denominator of q. If applied knowledge assets make a difference to stock market value, $\eta_t/\pi_t = \phi_t > 0$. I estimate equation (3) empirically using two panels of data, corporations in the sample for the 1910s and the 1920s. The objective is to determine how far the 1920s was an exceptional period in the historical context of the changing market value of patentable assets.

Equation (3) poses three estimation challenges. First, ϕ_t will be biased upward if firms with higher values of q survive longer and cite their own patents independently of the technological merit of the invention. To purge the data of any bias due to self-citations, I traced all 135 firms in the sample forward in time, documenting any mergers and name changes, giving a list of 60 companies that survived and were "at risk" of citing the 1910–1939 patents spuriously. I then matched this list against the population of patent assignee firms in the NBER data for 1975–1999 to isolate instances where surviving firms cited their own historical patents.[19] The matching process revealed that self-citations account for around 4 percent of the citations observed in the current sample. In all the econometrics that follow, these self-citations are removed.

Second, citations are measured as of a specific period in time, between 1975 and 1999 in the case of the NBER data. Truncation in the citation lag distribution, as illustrated in Figure 4, means that citations to patents in earlier years will be biased downward relative to those for later years. To address this problem I use the aggregate citation distribution to scale individual firm citation counts. Following Nick Bloom and Van Reenen (2002, 101), I assume that changes in the distribution given in Figure 4 are a function of time, and therefore the citations of the firms in the sample can be normalized using aggregate cites in each year. I adopt a benchmark year of 1925 and multiply individual firm citations at time t by the ratio of 1925 cites to cites at time t.[20]

[19] By contrast, to match my 60 surviving companies or their offshoots for the citations I collected from 1976–2006 would have required more than 200,000 additional hits of the USPTO's Web site to get assignee information. Given the USPTO has a restriction of 1,000 hits per day, I restricted the analysis to citations from the NBER data where assignee information is already collated into the dataset.

[20] For example, patents granted between 1975 and 1999 cited patents granted in 1910 13,549 times, and patents granted in 1925 26,236 times. The weighting factor for individual firms cites in 1910 is therefore 1.94. I chose 1925 as the benchmark year because it falls approximately halfway between 1910 and 1939.

This method adjusts for the loss of citations for the 1910s patents relative to the 1920s patents, and therefore estimates of ϕ_t are directly comparable across time periods.

The third challenge is the depreciation rate used to construct patent and citations stocks.[21] I follow standard practice in my empirical specifications and assume that the stock of patents G^{pat} and citations G^{cit} evolves according to the declining balance formulas $G_{it}^{pat} = (1 - \delta)G_{it-1}^{pat} + PATENTS_{it}$ and $G_{it}^{cit} = (1 - \delta)G_{it-1}^{cit} + CITATIONS_{it}$ with a customary depreciation rate $\delta = 0.15$. An annual depreciation rate of 15 percent, however, may be unduly high as the rate at which the citations should be reduced given the length of the lag between citing and cited patents. Long-lived inventions might be expected to depreciate less, and therefore I experiment with different values of δ in the estimating equations to test the robustness of the results. Hall, Jaffe, and Trajtenberg (2005, 24–25) note that alternate assumptions about the depreciation rate in q regressions lead to only small changes in the estimated coefficients on citation stocks. Equally, I find that, in the current sample, departures from the value of 0.15 have only a minor influence on the results.

B. *Excess Return Regressions*

Tobin's q regressions have proved to be the most tractable method for recovering estimates of the impact of knowledge assets on equity values, but the downside of the approach is potential aggregation bias, given that annual balance sheet data and year-end market price may be only a weak proxy for within-year changes in stock market value. Figure 5 reveals marked swings in the S&P Composite Index over relatively short event windows of the stock market, and to explore the changing market value of patentable assets during these periods I estimate monthly excess return regressions.

Break points in the time series illustrated in Figure 5 are defined by customary dates in the literature. Although there is usually disagreement about the timing and very existence of a bubble in the 1929 stock market, there is broad agreement concerning the chronology of the 1920s boom and bust. Frederick Lewis Allen (1931), a noted early twentieth century historian, dates the bubble from March 1928, while John Kenneth Galbraith writes in *The Great Crash* (1955, 11), that "early in 1928, the nature of the boom changed [as] the mass escape into make believe, so much a part of the true speculative orgy, started in earnest." Eugene White (1990) dates the bubble from March 1928 to Black Tuesday in October 1929, while the nadir of the crash was reached in the summer of 1932.

Based on this literature and Robert J. Shiller's (2000) calculations of the S&P Composite, I define four discrete time periods as follows: 1) the stock market *pre-runup*, December 1925[22] to February 1928; 2) the *runup*, March 1928 to September 1929; 3) the *crash*, October 1929 to June 1932; and 4) the *post-crash*, July 1932 to December 1939. I also examine the stock market's changing value of patentable assets over an additional five subperiods illustrated in Figure 5: 1) July 1932 to July 1933; 2) August 1933 to March 1935; 3) April 1935 to February 1937; 4) March 1937 to April 1938; and 5) May 1938 to December 1939. These subperiods are important in view of the punctuated stock market of the 1930s. Notably, in the third subperiod between April 1935 to February 1937 the S&P Composite Index almost doubled as economic conditions improved drastically prior to the recession of 1938 (Christina Romer 1992).

[21] Hall, Jaffe, and Trajtenberg (2005) make a distinction between a "past citations stock" and a "future citations stock" in samples where the citations keep coming past the firm year observation. Since all the citations in the current data fall into the "past citations stock" category, there is no need to make any adjustment for the kind of truncation that they describe.

[22] The runup period is truncated in December 1925 because of data availability from CRSP.

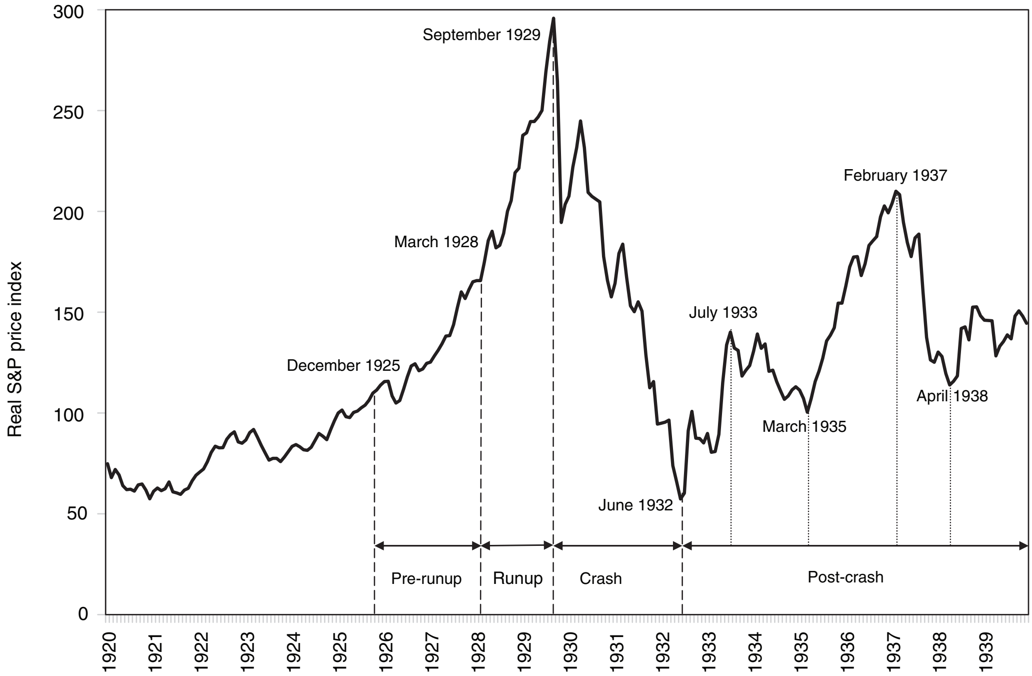

Figure 5. The Life Cycle of the 1929 Stock Market Crash

Notes: S&P series from Shiller (2000) with the index recalculated so that January 1925 = 100. Dates highlighted are for break points described in the text.

The estimating equation for excess returns takes the familiar form of

$$R_{it} - R_{ft} = \alpha_0 + \alpha_1 \log(SIZE)_{it-1} + \alpha_2 (B/M)_{it-1} + \alpha_3 R_{it-1,t-12} + \alpha_4 (G = 0)_{it} + \alpha_5 G_{it} + \alpha_6 G_{it=1929} + \varepsilon_{it}, \tag{4}$$

where $R_{it} - R_{ft}$ is the excess of the monthly return over the 30-day Treasury bill rate from Ibbotson Associates, and the regression purges any component of excess returns due to the risk premium associated with *SIZE*, the market value of common stock, *B/M*, the book-to-market value, and an additional control variable, $R_{it-1,t-12}$, the cumulative return over the prior 12 months. The objective is to determine if, net of these controls, changes in the market value of patentable assets explain any excess returns.

I estimate equation (4) by matching monthly equity and return data from CRSP with monthly patent totals for individual firms.[23] I use the same declining balance formula as in the q regression framework to calculate the stock of patents and citations, but with a depreciation rate $(1 - \delta)^{1/12}$ because the patent and citation counts are measured in monthly as opposed to annual totals. A dummy variable $G = 0$ is coded 1 for firms in the sample that did not patent at all. As outlined above, I weight individual firm citation counts by aggregate citation counts with a benchmark

[23] To calculate the monthly totals, I matched patent issue numbers for patents assigned to the firms in the sample with aggregate patent issue numbers from monthly editions of the *Official Gazette* of the USPTO.

year of 1925 so that the parameter estimates on citations stocks are directly comparable across time periods. Additionally, I construct a variable $G^{pat}_{it=1929}$, which is fixed as the stock of patents held by firm i on the eve of the crash, and a further variable $G^{cit}_{it=1929}$ for the stock of citations held at the same time. I use these variables in excess return regressions for the *post-crash* phase from July 1932 to December 1939 and the various subperiods of the 1930s stock market. The basic idea is to distinguish between any excess returns due to patentable assets as of September 1929 and those due to the accumulation of patentable assets that followed.

IV. Results

As a precursor to the regression results, Tables 2 and 3 report descriptive statistics. For the Tobin's q regressions I split the data into two panels—the 1910s and the 1920s—with the earlier decade benchmarking changes in the market value of patentable assets during the stock market runup. Due to the expansion of the corporate sector and the spread of financial disclosure over time, the 1920–1929 panel contains more observations as new firms are added, while four firms in the 1910s panel drop out of the 1920s panel.[24] I show that the results are robust to these compositional changes. Table 3 reports descriptives for the excess return regressions, which are estimated over shorter event windows around the Great Crash. These show the large effect of the stock market boom and bust on the market capitalization, book-to-market, and returns of the firms in the sample, although in line with Figure 3, the descriptives on patenting show that this activity was increasing even during the Depression years.

A. *Comparing the 1910s and the 1920s*

The main results from the Tobin's q regressions are presented in Tables 4A and 4B. The first column of each set of results for patent stocks with and without historical citations is a baseline specification. The second column tests for a higher market value premium in specific industries by adding industry dummies and interactions for chemicals, electricity, and mechanical sectors, with a residual category "other" acting as a control group.[25] For both sets of regressions I use a cluster adjustment to estimate the standard errors assuming serial correlation within firm units. The third column of each set of results includes fixed effects to control for permanent unobservable firm-level factors. In all the regressions I control for a time effect in the data using year dummies.

Beginning with the 1910s panel, the coefficient on the patent stock variable is statistically significant in the baseline specification without historical citations (column 1). The results imply that an additional unit of the firm's patent stock per million dollars of capital assets leads to a 0.44 percent increase in market value, or a 7.15 percent increase for a one-standard-deviation change. Because none of the coefficients on the industry interactions in column 2 is estimated precisely, the baseline result is not being driven by high market value returns in specific sectors. However, the third column of Table 4A shows that the coefficient on the patent stock variable reverses sign when fixed effects are introduced. The significant coefficient in column 1 may therefore be driven by omitted time-invariant characteristics, which militates against inferring a causal impact of patentable assets on stock market value during the 1910s.

[24] These firms are American Cotton Oil, General Chemical, International Silver, and Lackawana Steel.

[25] Including interaction terms allows the slope of the relationship between market value and the firm's patent stock to be different depending on the firm's industrial sector. I allocated firms to sectors based on a description of their business activities in Moody's.

Table 2—Descriptive Statistics for Tobin's q Regressions

	Panel 1910–1919	Panel 1920–1929
Number of firms	89	131
Firms with zero patents	21	28
Mean panel years per firm	8.7	8.9
Mean year of incorproation	1897	1901
	[8.79]	[11.94]
Total assets (\$m)	95.84	119.6
	[242.31]	[286.43]
K (\$m)	47.23	37.01
	[161.33]	[111.42]
Tobin's q	0.721	1.05
	[0.315]	[0.75]
	3.75	2.79
Patent stock/K	3.75	2.79
(Without historical citations)	[16.25]	[10.48]
Patent stock/K	0.58	0.80
(With historical citations)	[2.32]	[2.41]

Notes: Standard deviations in brackets. K is capital assets at replacement cost. Patent stock/K is the firms' stock of patents per million dollars of K, both without and with historical citation weightings.

Table 3—Descriptive Statistics for Monthly Excess Return Regressions

	Pre-runup (Dec. 1925 to Feb. 1928)	*Runup* (Mar. 1928 to Sep. 1929)	*Crash* (Oct. 1929 to Jun. 1932)	*Post-crash* (Jul. 1932 to Dec. 1939)
Size$_{t-1}$	115.82	217.45	169.61	160.01
	[281.74]	[546.63]	[454.86]	[418.63]
Book-to-market$_{t-1}$	0.80	0.57	2.23	1.56
	[1.46]	[0.97]	[6.27]	[3.76]
Return$_{(t-1,t-12)}$	0.17	0.29	-0.36	0.30
	[0.32]	[0.41]	[0.42]	[0.61]
Patent stock	3.83	4.45	5.22	6.53
(Without historical citations)	[11.70]	[15.08]	[16.23]	[18.60]
Patent stock	1.57	1.61	2.30	4.28
(With historical citations)	[5.14]	[5.25]	[7.07]	[12.46]

Notes: Standard deviations in brackets. Size is the market value of common stock, book-to-market is the ratio of the book-to-market value of common stock, and return is the cumulative return on common stock for the prior 12 months.

With respect to the historical citation estimates, columns 4 and 6 of Table 4A reveal that the coefficients in the baseline and fixed effects specifications are not significantly different from zero. The results in column 5 provide stronger evidence of interindustry variation in the market value of invention with a high premium in chemicals,[26] which is robust to a weighting scheme designed to control for differences in the effectiveness of patent protection across industries (see the Appendix for details). However, the large standard errors for the comparable estimates in column 2 show that this result is not consistent across different patent stock specifications. Overall, the 1910s regressions provide limited evidence of a robust statistical association between corporate patentable assets and stock market value.

[26] Relative to the control group "other," an additional unit of historical citations per million dollars of capital assets for firms in the chemicals industry boosts market value by 0.104 + 0.21 = 31.4 percent.

TABLE 4A—TOBIN'S q REGRESSION RESULTS FOR THE PANEL, 1910–1919

	Dependent variable log(q): Panel is 1910−1919					
	Without historical citations			With historical citations		
	(1)	(2)	(3)	(4)	(5)	(6)
Patent stock/K	0.0044	0.0675	−0.001	0.0216	0.1035	0.007
	[0.0013]***	[0.0470]	[0.0006]*	[0.0172]	[0.0400]**	[0.0055]
Patents = 0	−0.0473	−0.036		−0.0525	−0.0484	
	[0.0644]	[0.0684]		[0.0652]	[0.0679]	
Chemicals		0.0438			0.0548	
		[0.0886]			[0.0880]	
Electricity		0.1136			0.1116	
		[0.1839]			[0.1812]	
Mechanical		−0.037			−0.029	
		[0.0802]			[0.0805]	
Chemicals × (patent stock/K)		0.0502			0.21	
		[0.0552]			[0.0878]**	
Electricity × (patent stock/K)		−0.0532			−0.0626	
		[0.0475]			[0.0452]	
Mechanical × (patent stock/K)		−0.063			−0.0853	
		[0.0469]			[0.0427]**	
Observations	777	777	777	777	777	777
R^2	0.18	0.22	0.5	0.17	0.19	0.5
Time effects (yearly)	Yes	Yes	Yes	Yes	Yes	Yes
Firm effects	No	No	Yes	No	No	Yes

Notes: Standard errors in brackets. Significance at the *10 percent, **5 percent, and ***1 percent levels. In columns 1–3, the patent stock is calculated without historical citation weights, and in columns 4–6 with historical citation weights. All regressions include heteroskedasticity robust standard errors, which are also clustered by firm in columns 1–2 and 4–5.

TABLE 4B—TOBIN'S q REGRESSION RESULTS FOR THE PANEL, 1920–1929

	Dependent variable log(q): Panel is 1920−1929					
	Without historical citations			With historical citations		
	(1)	(2)	(3)	(4)	(5)	(6)
Patent stock/K	0.0021	0.0433	0.0067	0.0198	0.0582	0.0299
	[0.0025]	[0.0260]	[0.0029]**	[0.0167]	[0.0379]	[0.0088]***
Patents=0	−0.0757	−0.0462		−0.0634	−0.0548	
	[0.0794]	[0.0800]		[0.0808]	[0.0798]	
Chemicals		0.0002			0.0257	
		[0.1038]			[0.0968]	
Electricity		0.2231			0.1116	
		[0.0744]***			[0.0716]***	
Mechanical		−0.025			−0.0445	
		[0.0843]			[0.0864]	
Chemicals × (patent stock/K)		0.0553			0.0972	
		[0.0758]			[0.1207]	
Electricity × (patent stock/K)		−0.0264			−0.0123	
		[0.0265]			[0.0378]	
Mechanical × (patent stock/K)		−0.0421			−0.0457	
		[0.0266]			[0.0413]	
Observations	1,164	1,164	1,164	1,164	1,164	1,164
R^2	0.29	0.32	0.55	0.29	0.31	0.56
Time effects (yearly)	Yes	Yes	Yes	Yes	Yes	Yes
Firm effects	No	No	Yes	No	No	Yes

Notes: Standard errors in brackets. Significance at the *10 percent, **5 percent, and ***1 percent levels. In columns 1–3 the patent stock is calculated without historical citation weights, and in columns 4–6 with historical citation weights. All regressions include heteroskedasticity robust standard errors, which are also clustered by firm in columns 1–2 and 4–5.

The evidence of a robust relationship between these variables is much stronger in certain specifications for the 1920s. None of the industry interactions in Table 4B is positive, which indicates that patenting performance during these years is not just a proxy for "hot" sectors. A downside is that the baseline specifications are not significant at the customary levels, but the inclusion of firm fixed effects strengthens the relationship between patentable assets and Tobin's q. The coefficient in column 6 implies a 3 percent increase in q per unit change of a firm's stock of historical citations. The significance of fixed effects implies that "within-firm" as opposed to cross-sectional changes in patenting were an important determinant of changes in stock market value during this era, while the highly significant coefficient on historical citations suggests that investors were responding to signals about the quality of patented inventions. The fixed effects estimates are economically as well as statistically significant. Increasing historical citations for a patenting firm from the twenty-fifth percentile to the seventy-fifth percentile in the distribution equates to a 30.7 percent increase in its market value.

The magnitude of the fixed effects coefficient on the firm's stock of historical patent citations in column 6 of Table 4B holds when subjecting the data to robustness checks. Halving the value of the patent stock depreciation rate, δ, to 0.075 gives a similar estimate of 0.0286 (0.0085), while a coefficient of 0.0325 (0.0096) is estimated when $\delta = 0.30$. The difference in the estimates between periods (compare column 6 of Tables 4A and 4B) is not driven by any compositional change in the data. Restricting the 1920s regression to only those firms that are in the 1910s panel gives an estimate of 0.0285 (0.0094), which is only slightly smaller than the estimate for the full sample of firms. This estimate for the restricted sample compares directly with the coefficient of −0.0010 (0.0006) for the 1910s panel in column 6 of Table 4A. This comparison indicates a stronger empirical link between q and corporate patentable assets during the 1920s stock market boom.

B. *The Pre-Runup, Runup, Crash, and Post-Crash*

Turning to the excess return regressions, the objective is to use monthly data to examine the stock market's changing value of corporate patentable assets during shorter event windows around the Great Crash. Tables 5A to 5D present the results for the pre-runup, runup, crash, and post-crash phases. I follow the same approach of Tables 4A and 4B and report a baseline specification followed by regressions with industry dummies and interactions and fixed effects estimates. In contrast to the q regressions, I assume serial correlation within time as opposed to firm units to adjust the standard errors for clustering. Because equity returns are considerably less persistent than q, this assumption seems reasonable and it also yields larger standard errors and thereby reduces the risk of understating true coefficient variability.[27] In all the regressions I include monthly dummies to absorb time related effects.

Table 5A examines the relationship between equity returns and stocks of patents with and without historical citations during the pre-runup phase from December 1925 to February 1928. Interestingly, although the coefficients on the patent stock variable are positive, none is distinguishable from zero at the customary levels of significance, and there is no indication of industry specific effects. The results are consistent with the literature summarized by White (1990) which asserts that a break point in the stock market occurred later in 1928. There is no evidence during this particular event window that the knowledge capital of firms was earning excess returns.

[27] I report the largest standard errors after estimating the regressions with standard errors clustered by firm units and by time units. In the q regressions, clustering by firm units yields the largest standard errors, whereas clustering by time unit yields the largest standard errors in the excess return regressions.

TABLE 5A—EXCESS RETURN REGRESSION RESULTS FOR THE PRE-RUNUP PANEL

	Dependent variable $R_{it} - R_{ft}$: *Pre-runup* panel (Dec. 1925 to Feb. 1928)					
	Without historical citations			With historical citations		
	(1)	(2)	(3)	(4)	(5)	(6)
Log(SIZE)$_{t-1}$	0.0009	0.00136	−0.16102	0.00097	0.00152	−0.16135
	[0.00307]	[0.00314]	[0.02655]***	[0.00294]	[0.00315]	[0.02660]***
Book-to-market$_{t-1}$	0.00574	0.0058	0.00825	0.00575	0.00584	0.00815
	[0.00248]**	[0.00250]**	[0.01134]	[0.00250]**	[0.00251]**	[0.01134]
Return$_{(t-1,t-12)}$	0.01103	0.00843	−0.00868	0.01093	0.0086	−0.00886
	[0.00877]	[0.00832]	[0.02104]	[0.00869]	[0.00849]	[0.02106]
Patents = 0	−0.00973	−0.00974		−0.00976	−0.00981	
	[0.01005]	[0.01003]		[0.01014]	[0.01005]	
Patent stock	0.00007	0.00041	0.00015	0.00011	−0.00054	0.0004
	[0.00010]	[0.00107]	[0.00046]	[0.00016]	[0.00139]	[0.00052]
Chemicals		−0.00545			−0.00637	
		[0.01166]			[0.01129]	
Electricity		−0.02934			−0.02027	
		[0.01325]**			[0.01039]*	
Mechanical		−0.00454			−0.00515	
		[0.00945]			[0.00948]	
Chemicals × patent stock		0.00074			0.0023	
		[0.00179]			[0.00253]	
Electricity × patent stock		0.00007			0.00103	
		[0.00109]			[0.00120]	
Mechanical × patent stock		−0.00036			0.00065	
		[0.00104]			[0.00142]	
Observations	1,230	1,230	1,230	1,230	1,230	1,230
R^2	0.14	0.14	0.22	0.14	0.14	0.22
Time effects (monthly)	Yes	Yes	Yes	Yes	Yes	Yes
Firm effects	No	No	Yes	No	No	Yes

Notes: Standard errors in brackets. Significance at the *10 percent, **5 percent, and ***1 percent levels. In columns 1–3 the patent stock is calculated without historical citation weights, and in columns 4–6 with historical citation weights. All regressions include heteroskedasticity robust standard errors, which are also clustered by time in columns 1–2 and 4–5.

In contrast, an important result to emerge from the runup panel from March 1928 to September 1929 is the size and precision of the estimated coefficients on the patent stock variable, especially in the specifications with historical patent citations. Column 4 of Table 5B implies annualized excess returns of 1.32 percent per unit of a firm's stock of historical citations, or 10.4 percent per standard deviation when the returns are cumulated over the 18-month window of the runup.[28] A further insight into the economic magnitude of the estimates can be gained by the coefficient on *Patents* = 0. Across the specifications, the estimates in Table 5B imply that zero patenting firms underperformed otherwise similar stocks by 33–38 percent during the 18-month stock market runup. There is no evidence of a significant difference across industries, as the offset coefficients for chemicals, electricity, and mechanical sectors in column 5 of Table 5B are all in a similar range. Column 6 shows that the baseline result is robust to the presence of a fixed firm effect in the data, albeit only at the 10 percent confidence level.

Corporate holdings of patentable assets were a key driver of equity returns during the late 1920s stock market runup, but the results in Table 5C suggest they were far less influential as a cause of the Great Crash. The fourth column of Table 5C reveals annualized excess returns of −0.72 percent per unit of a firm's stock of historical citations, or excess returns that are

[28] This result is robust to varying the patent stock depreciation rate. Halving the depreciation rate from 0.15 to 0.075 gives annualized excess returns of 1.31 percent per unit of a firm's stock of historical citations, or the same 1.32 percent when the depreciation rate is 0.30.

TABLE 5B—EXCESS RETURN REGRESSION RESULTS FOR THE RUNUP PANEL

	Dependent variable $R_{it} - R_{ft}$: *Runup* panel (Mar. 1928 to Sep. 1929)					
	Without historical citations			With historical citations		
	(1)	(2)	(3)	(4)	(5)	(6)
Log(SIZE)$_{t-1}$	0.00227	0.00217	−0.11464	0.00199	0.00166	−0.11434
	[0.00283]	[0.00300]	[0.02637]***	[0.00288]	[0.00308]	[0.02642]***
Book-to-market$_{t-1}$	0.00541	0.00598	0.02388	0.00533	0.00592	0.02355
	[0.00631]	[0.00655]	[0.03030]	[0.00639]	[0.00657]	[0.03032]
Return$_{(t-1,t-12)}$	0.02981	0.02481	0.04437	0.02958	0.02489	0.04335
	[0.01049]**	[0.01103]**	[0.01990]**	[0.01050]**	[0.01104]**	[0.01996]**
Patents = 0	−0.01885	−0.02092		−0.01849	−0.01963	
	[0.00724]**	[0.00674]**		[0.00728]**	[0.00694]**	
Patent stock	0.00028	−0.00139	0.0001	0.0011	−0.00286	0.00164
	[0.00017]	[0.00171]	[0.00053]	[0.00042]**	[0.00151]*	[0.00089]*
Chemicals		0.01837			0.0144	
		[0.01282]			[0.01084]	
Electricity		0.00954			0.0066	
		[0.00999]			[0.00972]	
Mechanical		0.01835			0.01783	
		[0.00635]**			[0.00561]***	
Chemicals × patent stock		0.00068			0.0046	
		[0.00226]			[0.00274]	
Electricity × patent stock		0.00169			0.00422	
		[0.00164]			[0.00149]**	
Mechanical × patent stock		0.00159			0.00384	
		[0.00168]			[0.00156]**	
Observations	1,509	1,509	1,509	1,509	1,509	1,509
R^2	0.24	0.24	0.28	0.24	0.25	0.28
Time effects (monthly)	Yes	Yes	Yes	Yes	Yes	Yes
Firm effects	No	No	Yes	No	No	Yes

Notes: Standard errors in brackets. Significance at the *10 percent, **5 percent, and ***1 percent levels. In columns 1–3 the patent stock is calculated without historical citation weights, and in columns 4–6 with historical citation weights. All regressions include heteroskedasticity robust standard errors, which are also clustered by time in columns 1–2 and 4–5.

insignificantly different from zero when firm fixed effects are introduced. The crash was not about correcting misalignments between high-technology and low-technology firms. While positive, the coefficient for zero patenting firms (*Patents* = 0) is not significant at the customary levels across any of the excess return specifications. Patent capital in the chemicals industry held its value well during the market's downturn, as evidenced by the industry interactions, which are precisely estimated in columns 2 and 5 of Table 5C.[29]

Nonetheless, the results do suggest a persistent effect of the stock market crash on investor reactions to patentable assets. Figure 3 shows that the firms in the sample continued to patent heavily during the 1930s, but Table 5D reports no significant effect of patent stocks on excess returns from July 1932 through December 1939 in the baseline, industry interaction, or fixed effects regressions. This holds true even when controlling for the stock of patents held on the eve of the crash through the variable *Patent Stock* 1929. Compared to the crash panel, the coefficients on *Patents* = 0 reverse sign, although the estimates are insignificantly different from zero. This result runs contrary to the runup result in Table 5B, where zero patenting firms strongly underperformed otherwise similar stocks.

[29] The results are very similar when using Cohen, Nelson, and Walsh weights as outlined in the Appendix. For example, the estimates in column 5 of Table 5C on the chemical, electricity, and mechanical interactions become 0.0071, 0.0049, and 0.0055, respectively.

Table 5C—Excess Return Regression Results for the Crash Panel

	Dependent variable $R_{it} - R_{ft}$: *Crash* panel (Oct. 1929 to Jun. 1932)					
	Without historical citations			With historical citations		
	(1)	(2)	(3)	(4)	(5)	(6)
Log(SIZE)$_{t-1}$	0.00264	0.00278	−0.04744	0.00293	0.00283	−0.04728
	[0.00320]	[0.00325]	[0.01175]***	[0.00322]	[0.00319]	[0.01175]***
Book-to-market$_{t-1}$	0.00193	0.00201	0.00387	0.00194	0.00191	0.00386
	[0.00112]	[0.00105]*	[0.00165]**	[0.00112]	[0.00107]	[0.00165]**
Return$_{(t-1,t-12)}$	−0.00986	−0.02122	−0.04695	−0.01061	−0.01934	−0.04768
	[0.02112]	[0.02142]	[0.01324]***	[0.02117]	[0.02124]	[0.01326]**
Patents = 0	0.00465	0.00613		0.00441	0.00742	
	[0.00775]	[0.00674]		[0.00768]	[0.00690]	
Patent stock	−0.00017	−0.00629	−0.00014	−0.0006	−0.00577	−0.00087
	[0.00011]	[0.00141]***	[0.00030]	[0.00025]**	[0.00128]***	[0.00058]
Chemicals		−0.03402			−0.0317	
		[0.01022]***			[0.01000]***	
Electricity		0.0086			0.00779	
		[0.01205]			[0.01046]	
Mechanical		−0.02317			−0.02038	
		[0.00646]***			[0.00663]**	
Chemicals × patent stock		0.00712			0.00733	
		[0.00180]***			[0.00164]***	
Electricity × patent stock		0.00596			0.005	
		[0.00143]***			[0.00125]***	
Mechanical × patent stock		0.00623			0.00544	
		[0.00158]***			[0.00149]***	
Observations	2,530	2,530	2,530	2,530	2,530	2,530
R^2	0.48	0.49	0.51	0.48	0.49	0.51
Time effects (monthly)	Yes	Yes	Yes	Yes	Yes	Yes
Firm effects	No	No	Yes	No	No	Yes

Notes: Standard errors in brackets. Significance at the *10 percent, **5 percent, and ***1 percent levels. In columns 1–3 the patent stock is calculated without historical citation weights, and in columns 4–6 with historical citation weights. All regressions include heteroskedasticity robust standard errors, which are also clustered by time in columns 1–2 and 4–5.

Because the insignificance on the variables of interest in the post-crash panel might be driven by biases induced by measuring long-run horizon returns, Table 5E reports the same specification in the final column of Table 5D for shorter subperiods of the 1930s stock market as illustrated in Figure 5.[30] While none of the *Patents* $= 0$ coefficients is estimated precisely, the results show the effect of patent stocks on excess returns is stronger during the pronounced rebound, and almost doubles the S&P Composite Index between April 1935 and February 1937. Column 3 implies annualized excess returns of 0.82 percent per unit of a firm's stock of historical patent citations. Interestingly, the estimate of annualized excess returns increases to a statistically more significant 0.90 percent when the control variable *Patent Stock* 1929 is dropped.[31] That is, returns are somewhat higher and more precisely estimated when rolling in pre-crash patents

[30] A number of biases have been noted in the analysis of long horizon returns, such as survivorship or skewed returns which can distort t-statistics either upward or downward (see John D. Lyon, Brad M. Barber, and Chih-ling Tsai 1999). A solution in the spirit of Mark Mitchell and Erik Stafford (2000) would be to construct matched size and book-to-market portfolios for benchmarking returns. This, however, would require a considerable data collection exercise from Moody's to obtain size and book-to-market variables for the population of publicly traded firms so that matched portfolios could be constructed. The biases this method addresses are considerably less problematic when estimating shorter period returns as in Table 5E.

[31] When dropping *Patent Stock* 1929, the comparable coefficient to that in column 3 of Table 5E is 0.00075, which is significant at better than the 1 percent level.

TABLE 5D—EXCESS RETURN REGRESSION RESULTS FOR THE POST-CRASH PANEL

	Dependent variable $R_{it} - R_{ft}$: *Post-crash* panel (Jul. 1932 to Dec. 1939)							
	Without historical citations				With historical citations			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(SIZE)$_{t-1}$	−0.00447	−0.00429	−0.04254	−0.00422	−0.0047	−0.00454	−0.04255	−0.00472
	[0.00241]*	[0.00254]	[0.00685]***	[0.00244]	[0.00249]*	[0.00261]	[0.00685]***	[0.00250]*
Book-to-market$_{t-1}$	0.00338	0.00344	0.0063	0.00346	0.00335	0.00342	0.0063	0.00335
	[0.00128]**	[0.00128]**	[0.00159]***	[0.00129]**	[0.00127]**	[0.00128]**	[0.00159]***	[0.00127]**
Return$_{(t-1,t-12)}$	−0.02441	−0.02679	−0.02485	−0.02645	−0.02459	−0.02671	−0.02479	−0.0246
	[0.01018]**	[0.01075]**	[0.00668]***	[0.01075]**	[0.01020]**	[0.01069]**	[0.00667]***	[0.01020]**
Patents = 0	−0.00549	−0.00487	−0.00567	−0.00515	−0.00456	−0.00515		
	[0.00661]	[0.00618]	[0.00664]	[0.00656]	[0.00634]	[0.00655]		
Patent stock	0.00016	0.00136	−0.0001	0.00008	0.00032	0.00092	0.00011	0.0004
	[0.00012]	[0.00198]	[0.00017]	[0.00019]	[0.00021]	[0.00110]	[0.00020]	[0.00030]
Patent stock 1929				0.0001				−0.00027
				[0.00017]				[0.00047]
Chemicals		0.01011				0.00925		
		[0.00757]				[0.00664]		
Electricity		−0.00022				0.00058		
		[0.00844]				[0.00752]		
Mechanical		0.01373				0.01305		
		[0.00698]*				[0.00663]*		
Chemicals × patent stock		−0.00109				−0.00037		
		[0.00188]				[0.00096]		
Electricity × patent stock		−0.00122				−0.00069		
		[0.00194]				[0.00103]		
Mechanical × patent stock		−0.00123				−0.00061		
		[0.00187]				[0.00098]		
Observations	6,449	6,449	6,449	6,449	6,449	6,449	6,449	6,449
R^2	0.55	0.55	0.56	0.55	0.55	0.55	0.56	0.55
Time effects (monthly)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm effects	No	No	Yes	No	No	No	Yes	No

Notes: Standard errors in brackets. Significance at the *10 percent, **5 percent, and ***1 percent levels. In columns 1−4 the patent stock is calculated without historical citation weights, and in columns 5−8 with historical citation weights. All regressions include heteroskedasticity robust standard errors, which are also clustered by time in columns 1−2 and 4 and 5−6 and 8.

which suggests, alongside the results in Table 5B, that the late 1920s stock market did value assets that were important.

V. Conclusion

Conventionally the 80.6 percent drop in the S&P Composite Index from 1929 peak to 1932 trough has been seen as an outcome of speculation and investor irrational exuberance (DeLong and Shleifer 1991; Shiller 2000). The alternative view that the late 1920s stock market was not overvalued, which was stressed at the time by Fisher (1930) and more recently in McGrattan and Prescott (2004), has emphasized that market values on the eve of the crash were high because investors were pricing intangibles like new technology. Because these assets have eluded direct measurement, however, we do not know if they were driving equity prices upward, or how investors were responding to new technology after the market had fallen sharply.

The data assembled here have been used to address both of these issues. A central finding is that the pricing of corporate stocks of patentable assets conveys important information about changes in stock market value, especially when using historical patent citations to identify the technological significance of inventions. Since lagged citations provide a perfect hindsight

Table 5E—Excess Return Regression Results for Subperiods of the 1930s

	Dependent variable $R_{it} - R_{ft}$ with historical citations				
	Jul. 1932 to Jul. 1933 (1)	Aug. 1933 to Mar. 1935 (2)	Apr. 1935 to Feb. 1937 (3)	Mar. 1937 to Apr. 1938 (4)	May. 1938 to Dec. 1939 (5)
Log(SIZE)_{t-1}	–0.02533	0.00285	–0.0079	0.00567	–0.00259
	[0.01540]	[0.00602]	[0.00377]*	[0.00363]	[0.00415]
$\text{Book-to-market}_{t-1}$	0.00325	0.00185	–0.00019	0.00265	0.00088
	[0.00201]	[0.00257]	[0.00140]	[0.00088]**	[0.00244]
$\text{Return}_{(t-1,t-12)}$	–0.06213	0.00897	–0.00355	–0.03825	–0.06723
	[0.03211]*	[0.00962]	[0.01365]	[0.02785]	[0.03314]*
Patents = 0	–0.00296	0.00137	–0.00372	0.01517	0.00326
	[0.03072]	[0.01090]	[0.00559]	[0.00887]	[0.00656]
Patent stock	0.00111	–0.00018	0.00068	–0.0001	0.00014
	[0.00190]	[0.00038]	[0.00034]*	[0.00030]	[0.00012]
Patent stock 1929	–0.00108	0.00015	0.00025	–0.00029	–0.00013
	[0.00241]	[0.00058]	[0.00069]	[0.00084]	[0.00039]
Observations	888	1,456	1,633	994	1,402
R^2	0.57	0.46	0.17	0.65	0.57
Time effects (monthly)	Yes	Yes	Yes	Yes	Yes
Firm effects	No	No	No	No	No

Notes: Standard errors in brackets. Significance at the *10 percent, **5 percent, and ***1 percent levels. In all columns the patent stock is calculated with historical citation weights. All regressions include heteroskedasticity robust standard errors, which are also clustered by time.

measure of patent quality, the results suggest that investors were sophisticated in their market pricing decisions. A large difference in the payoffs for innovation between the 1910s and the 1920s is consistent with the historical evidence that the 1920s was an extraordinary period of technological progress. Given how large was the fraction of knowledge capital to physical capital at this time, the increase in the valuation of patent capital was an important driver of the 1920s stock market runup.

In contrast, the changing market value of patentable assets was not a key explanatory factor in the Great Crash. For this event window, the excess return coefficients are less precise and smaller in economic magnitude when compared against the late 1920s runup. This finding is aligned with the literature that implies the crash was exaggerated by influences other than any mispricing of the knowledge capital held by firms. For example, Stephen Cecchetti (1998) argues that by pressurizing banks to restrict the supply of credit and raising interests rates to curb speculation, the Federal Reserve's preemptive strike against the perceived stock market bubble "clearly led to a disastrously contradictory path for policy" (178).

Despite the Great Crash and the slide into the Depression, the 1930s was not a technologically moribund decade. Firms in this study accumulated substantial post-crash quantities of influential patents, which had a real effect on productivity (Field 2003). Why did the market value of these assets experience only a stunted recovery after equity prices had initially faltered? Galbraith (1955, 171), writing about a psychological crisis in confidence, states "the ensuing collapse automatically destroys the very mood speculation requires." The literature suggests further culprits as well: cartelization induced by New Deal policies (Harold Cole and Lee Ohanian 2004); the increased marginalization of shareholder interests (Adolf Berle and Gardiner Means 1932); and social and political angst as manifest in increased worker militancy, discontent over Hoovervilles, and the "Red Scare" (Robert Merton 1987; G. William Schwert 1990; Joachim Voth 2005). Whatever innovation had done during the 1920s to create positive expectations about additions to future free cash flow, it was much more of a sideshow in the stock market of the 1930s.

Appendix: Cohen, Nelson, and Walsh Regression Weights

The regressions with industry dummies and interactions assume that the propensity to patent across industries is the same. As a robustness check, I weighted the patent stocks according to the effectiveness of patent protection across industries as reported in Cohen, Nelson, and Walsh (2000). I use a weighting scheme based on their Tables 1 and 2. I merge their industries into mine and calculate the average share of both product and process innovations that are patented giving shares of 30.96 percent, 22.93 percent, 30.77 percent, and 26.32 percent for my sectors chemicals, electricity, mechanical, and other, respectively. I then normalize on "other" so as to change only the interaction terms in the regression and multiply the patent stocks for companies in each sector by the resulting values: 1.18 for chemicals, 0.87 for electricity, and 1.17 for mechanical. Table A1 presented below reports the results in column 5 of Tables 4A and 4B alongside the same regression estimated with weights.

Table A1—Industry Interactions with Cohen, Nelson, and Walsh Regression Weights

	Dependent variable log(q) Panel 1910–1919 with historical citations		Dependent variable log(q) Panel 1920–1929 with historical citations	
	No CNW weights	CNW weights	No CNW weights	CNW weights
Patent stock/K	0.1035	0.1035	0.0582	0.0582
	[0.0400]**	[0.0400]**	[0.0379]	[0.0379]
Patents = 0	–0.0484	–0.0484	–0.0548	–0.0548
	[0.0679]	[0.0679]	[0.0798]	[0.0798]
Chemicals	0.0548	0.0548	0.0257	0.0257
	[0.0880]	[0.0880]	[0.0968]	[0.0968]
Electricity	0.1116	0.1116	0.2147	0.2147
	[0.1812]	[0.1812]	[0.0716]***	[0.0716]***
Mechanical	–0.029	–0.029	–0.0445	–0.0445
	[0.0805]	[0.0805]	[0.0864]	[0.0864]
Chemicals × (patent stock/K)	0.21	0.163	0.0972	0.0739
	[0.0878]**	[0.0764]**	[0.1207]	[0.1044]
Electricity × (patent stock/K)	–0.0626	–0.0565	–0.0123	–0.0055
	[0.0452]	[0.0467]	[0.0378]	[0.0378]
Mechanical × (patent stock/K)	–0.0853	–0.0874	–0.0457	–0.0471
	[0.0427]**	[0.0420]**	[0.0413]	[0.0405]
Observations	777	777	1,164	1,164
R^2	0.19	0.19	0.31	0.31
Time effects (yearly)	Yes	Yes	Yes	Yes
Firm effects	No	No	No	No

Notes: Standard errors in brackets. Significance at the *10 percent, **5 percent, and ***1 percent levels. All regressions include heteroskedasticity robust standard errors clustered by firm.

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