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INTERNET HISTORIES
https://doi.org/10.1080/24701475.2020.1747261

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ABSTRACT

Rigorous research into the historical past of Web technology-driven innovation becomes timely as technological growth and forecasting are attracting popular interest. Drawing on economic and management literature relating to the typical trends of technological innovation, we examine the long-term development of Web technology in a theoretically informed and empirical manner. An original longitudinal dataset of 20,493 Web-related US patents is used to trace the growth curve of Web technology between the years of 1990 through 2013. We find that the accumulation of corporate Web inventions followed an S-shaped curve which shifted to linear growth after year 2004. This transition is unusual in relation to the traditional S-curve model of technological development that typically approaches a limit. The point of inflection on the S-curve coincided reasonably closely with the timing of the dot-com crash in year 2000. Moreover, we find a complex bi-directional relationship between patenting rates in Web technology and movements in the NASDAQ composite stock index. The implications of these results are discussed in theoretical and practical terms for sustained technological growth. Specific recommendations for different stakeholders in commercial Web development are included.

ARTICLE HISTORY
Received 26 November 2019
Revised 25 February 2020
Accepted 23 March 2020

KEYWORDS
Web technology; innovation; technological revolutions; patents; empirical measurement

1. Introduction

Last year we celebrated the 30*th* anniversary of the Web. Such landmarks offer natural opportunities to reflect on the formative years of a major technology industry. Previous celebrations marking the Web at 20 (Hall & Tiropanis, 2012; Husemann & Rudin, 2012), 25 (Brügger, 2016) and Web Science at 10 (Hall et al., 2017) evidence the wide ranging interest in viewing the Web from a retrospective angle. However, despite a growing corpus of careful historical research about the development of the Web (Brügger, 2018; Brügger & Laursen, 2019), there remain areas of popular discourse that would benefit from greater theoretical context and empirical evidence.

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Supplemental data for this article can be accessed at https://doi.org/10.24433/CO.9866432.v1.

Informal observations can serve as a valuable starting point for exploring topics that are compelling to the Web community. Technical experts have remarked that "the Web has grown exponentially, reaching far beyond its original technical foundations" (Hall et al., 2017). Powerful statements like this express the transformative impact of the Web, but they also pose methodological and disciplinary challenges for the discernment of empirical trends. Our article takes a step towards operationalising the question of technological growth on the Web by measuring a particular aspect of its commercial history.

We position our research in the field of innovation studies, where the notion of technological growth will be addressed in a corporate context. We view innovation as the process through which new ideas or methods are generated by firms with the intention of creating economic value. Technological innovation specifically is understood here as the creation of ideas relating to technology; this includes developments within the technical components themselves or novel ways of applying existing technologies to carry out business functions. By technological growth, we mean the accumulation of such innovations as driven by industry.

Our article aligns with two key themes from the fields of innovation studies and economic history:

1. **The shape of technological growth in the commercial Web**. While some futurists argue for the reality of ever-accelerating exponential growth in technologies (Kurzweil, 2014), an S-shaped model that approaches a limit has more commonly been used in the fields of economics and management (Modis, 2006). This model too begins with an exponential trend, but the rate of growth eventually starts to decline and level off. Different variations of this pattern have been observed in empirical settings, making it difficult to anticipate the growth curve of a particular technology. Our first aim is to reveal the growth trajectory of corporate Web innovations.
2. **The link between waves of technological innovation in the Web and stock market movements**. Periods of rapid technological growth have historically been associated with the development and collapse of speculative investment bubbles. The economic boom and crash of year 2000 is frequently mentioned in connection with the Web industry (Atkinson et al., 2010; O'Reilly, 2007; Perez et al., 2010), but this association has not yet been verified quantitatively. We examine the link between corporate innovation in Web technology and stock market movements over time.

The Web is a global phenomenon encompassing inventions from a diverse collection of industrial economies. Among them, the US has arguably held a pioneering position in terms of commercial applications and technical infrastructure, as well as a strong research community working with domestic and foreign inventions (Mowery & Simcoe, 2002). We focus our study on the US for this reason. Moreover, the US provides pragmatic benefits for us as researchers in terms of free computational access to innovation data from patent records[1]. Patents are a valuable indicator that has typically been used in economic studies of technological change.

Our longitudinal study of Web-related patents offers a novel contribution to Web historiography. One of the main challenges in this field is the degree to which digital artefacts and practices have been preserved. Sources of data from the Web's past tend to be transitory and ephemeral, as exemplified by the many commercial websites and Flash applications that vanished after the dot-com crash (Ankerson, 2012). In materials that have been archived, further challenges are presented by selection bias. Decisions about what to archive and what not to archive can overtly or inadvertently be influenced by imbalances of power (e.g. in terms of gender, marginal groups and the experiences of ordinary users) (Ankerson, 2012). Such issues of data loss or omission are circumvented in commercial patent records, whose preservation and stewardship have already been addressed to a large extent by national government agencies.

The focus on US patents positions our study in a specifically corporate, commercialised Web context that lies within a closed innovation paradigm. In doing this, we overlook other important forms of growth in the Web, such as user participation and adoption, as well as open source and non-market-driven innovation. Previous historical studies in these areas have drawn insights from empirical indicators such as archived webpages (Rogers, 2017; Sykora, 2017), social networking infrastructures (Helmond et al., 2019), mailing lists (Hocquet & Wieber, 2018) and transnational networks of people and organisations that contributed to the expansion of the Internet (Siles, 2018). Growth of Internet software especially has been the subject of substantial literature on the importance of open innovation, where technologies are generative through being tinkered with or modified by anyone (Zittrain, 2008). Patents, on the other hand, are filed with a specific commercial intent that restricts the use of existing knowledge to develop novel technologies. They enable firms to achieve certain private advantages at the expense of collective innovative progress and aggregate information production (Benkler, 2002; Von Hippel, 2005). Despite these critical considerations, it is not our aim to make value judgments about which strategies accelerate or hamper innovation. Rather, our intention in this article is to show the historical dimension of Web technology patents and how they relate to the commercial evolution of the Web.

Through the use of an original longitudinal dataset of Web-related patents, we contribute a quantitative analysis of Web technology growth in an economic and corporate context. We show how Web development was consistent with the trends exhibited by other technologies introduced before the Web, as well as highlighting unusual properties. Specifically, we observe unexpected continued growth that may be attributable to the unique characteristics of Web technology in terms of socio-technical aspects, open standards and complementary technological advances. Based on our interpretation of the findings, we provide recommendations for policy-makers, technology strategists, investors and communities involved in corporate Web development.

The article is structured as follows. Section 2 provides an overview of concepts used to theorise technological development. We then discuss why patent records are an appropriate signal for examining technological change in the Web industry. Our methodological approach begins in Section 3, where we use US patent records to gather a longitudinal dataset of inventions related specifically to the Web. Using these data, we create a growth curve for Web technology and examine association between patenting rates in Web technology with NASDAQ stock market movements. Our results are presented in Section 4 and discussed in Section 5. The implications are provided in Section 6.

2. Background

Previous historical studies have paid careful attention to the specific time, space and culture of events and artefacts generated through the Web. Such works have been important in addressing the extreme complexity and diversity of technologies embedded in human societies. However, if we take a step back and look at these patterns from a greater distance, it is intriguing to discern broader analogies with other spheres of technological development at different points in time. Specifically, we draw attention to empirical regularities in periods of economic growth and decline in past technological revolutions. This approach fits with a historical social science that is analytical, where unifying theories can be tested with data generated by history (Turchin, 2008).

It is already apparent that the impact of the Web is comparable to that of other technological revolutions which are recognized as being of great historical significance. The Web is a general purpose technology that permeates many aspects of our life, including the realms of academia, commerce, entertainment, politics and travel. When drawing historical analogies, economists discuss the Web alongside other technological revolutions, such as the mechanization of agriculture and manufacturing, the age of railways, heavy engineering and automobiles (Arthur, 2002; Perez et al., 2010). Technological revolutions have been defined as radical breakthroughs that form "a major constellation of interdependent technologies; a cluster of clusters or a system of systems" (Perez, 2010). The Web too produced a "network of networks" that encompasses interdependent relations between people, content, technologies and services on a global scale (Hall & Tiropanis, 2012). With this came a democratised division of labour among innovators in the network, creating a shift away from hierarchically regulated forms of innovation that were typical of proprietary systems (Von Hippel, 2005). In historical terms, the Web arguably reflects the essence of modernity, a transition from social orders defined by hierarchies of rank and class towards a more functional differentiation that relies on the interdependence of specialised forms of activity (Buzan & Lawson, 2015). By decentralising the dissemination of knowledge, the Web has impacted power relations across multiple levels of society. The mode of power in global economies has also been shifted into one that relies increasingly on knowledge (Mowery & Simcoe, 2002).

By considering the Web as a revolutionary configuration, we are able to compare it to previous technological revolutions and identify some of the aspects that make it unique. Below we discuss the theoretical foundations behind the S-shaped pattern that is typically used to describe economic growth during technological revolutions, as well as the association between innovation and economic indicators. In order to carry out an empirical examination of these topics, we describe the use of patents as a measurable indicator of technological innovation.

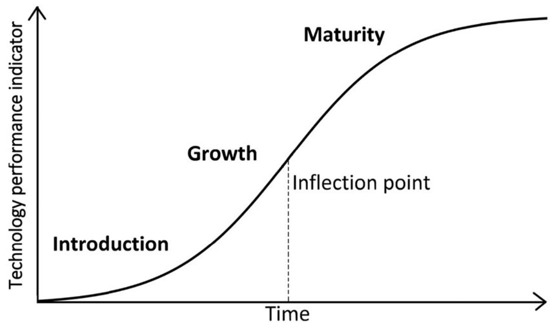

Figure 1. Typical technology S-curve.

2.1. Technology S-curves

Technological revolutions occur in cyclical patterns where periods of gradual change are interrupted by feverish outbursts of innovation. In an evolutionary context, these episodic events have been described using the term "punctuated equilibrium" (Mokyr, 1990), capturing the relation between slow and fast phases of technological development. This pattern can be represented graphically by an S-shaped curve that traces the introduction, growth and maturity of a technology over time. A depiction of the canonical S-curve as it relates to different technology phases is presented in Figure 1 and similar stylisations can be found in the literature (Andersen, 1999; Nieto et al., 1998; Taylor & Taylor, 2012).

S-curves have been identified at various scales and units of analysis across industries. Processes such as the diffusion of entrepreneurial activity (E. M. Rogers, 2010), technological substitution (Fisher & Pry, 1971), accumulated inventions (Andersen, 1999), and improvement in technological performance (Nieto et al., 1998) have produced S-shaped curves. When applied to the development of industries, each part of the S-curve has been linked to distinct forms of innovation, management and investment activity.

At the *introduction* of a technology, changes occur slowly. Years of gestation may be required for an emerging technology to realize widespread acceptance and commercial importance. In the case of the Web, this slow phase began in the late 1980s inside the specialist research domain of physicists working at CERN (Berners-Lee, 1999). By satisfying the users' needs in such niche market segments, a fledgling technology improves its functionality or cost before reaching mainstream users (Adner & Levinthal, 2002). The Web began this transition in the early 1990s, where it was deployed alongside other systems such as Gopher during the movement for campus-wide information systems at universities (Frana, 2004).

The *growth* phase is accelerated by exposure to the mass market, where the technology becomes a more compelling target for investment and innovation. Extension into commercial and home markets was implicated in the growth of the Web, leading to a boom in investment and subsequent innovation after the mid 1990s. Such times of growth from the peripheral to mainstream markets are characterized by intense exploration that leads to a rapid proliferation of new products and companies (Klepper, 1997; Perez, 2010).

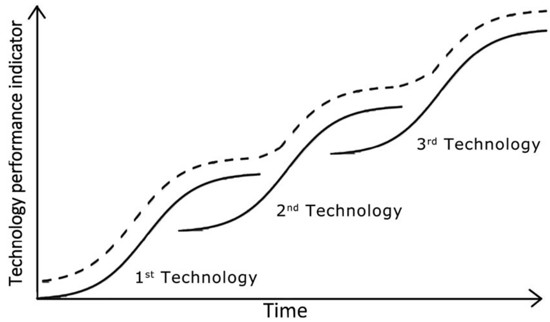

Figure 2. Successive S-curves in technological development. The dotted line shows the overall growth trajectory produced by component technologies. Adapted from Christensen (1992).

As an industry begins to *mature*, the pace of technological development typically slows down due to approaching limits of performance and diffusion in a saturating market. Instead of focusing on innovation and exploration, firms shift their attention to exploiting existing technological opportunities (Perez et al., 2010). Production processes become more rigid and efficient, making it increasingly difficult for established firms to accommodate radical innovation (Abernathy & Utterback, 1978).

The industry life cycle phases described above appear to follow a logical pattern reflective of the S-curve, but the universality of this representation has been challenged by empirical evidence. The performance trajectories of some technologies are poorly approximated by a single S-curve, yielding instead a fractal structure composed of several cascading S-curves (Chang & Baek, 2010; Modis, 1994; Sood & Tellis, 2005). This occurs when firms develop their technology by continuously substituting existing technological components with emerging technologies that have superior performance. For example, the disc drive industry had successive technologies with ferrite heads followed by thin film heads and later magneto-resistive heads (Christensen, 1992). Figure 2 demonstrates visually the possible growth trajectory created by this pattern of technological substitutions. A similar trend could apply to the development of Web technology, whose reliance shifted from residential Internet connectivity to wireless and mobile broadband, extending also from personal computers to smart mobile devices (Hall & Tiropanis, 2012).

Another way to consider successive technological phases is through the concept of *dominant design* (Anderson & Tushman, 1990). This refers to the technological properties of an industry that become stabilised after its initial stages of growth. In software industries, dominant designs become established through standards for applying existing technical fundamentals (Kim et al., 2017). Standards help new entrants to produce complementary goods and services that stimulate continued growth of the technology sector.

The long-term growth of Web technology has been supported by the World Wide Web Consortium (W3C) - a standardisation body that has operated since 1994. W3C provides guidelines and protocols that are open, flexible and interoperable (Berners-Lee, 1999). By continuously ensuring that Web standards are amenable to new applications and market niches, W3C may have raised the maximum capacity of adopters and engineering resources available for the further advancement of Web technology. The possibility of extended growth past the ceiling of a typical S-curve is therefore important to examine empirically in this context.

2.2. Innovation and stock market run-ups

Different phases of innovation during technological revolutions have traditionally been linked to cyclical movements in the economy (Schumpeter, 1934). The first half of the S-curve contains rapid technological growth that fuels enthusiastic speculation by investors, whose sentiments are affected by the intangible assets offered by an emerging industry (Wheale & Amin, 2003). In the absence of information on company performance, knowledge of fundamental technological advances and inventions can help investors to evaluate the potential gains of new ventures (Useche, 2014).

This applies to the development of the Web, where investors' beliefs in Web technology as a powerful driver of economic advancement created a euphoria for e-business stocks after the mid 1990s (King, 2000). Because such investment decisions were not founded on realistic projections of company profitability, they contributed to the formation of a "bubble" that was unsustainable over the long-term (Shiller, 2000). When positive financial speculation exceeds the actual earnings generated by technology firms, a period of market correction inevitably follows. Thus, the stock market collapse of 2000 led investors in Internet software to become more rational and cautious in their decisions. Typically, this shift becomes evident during the inflection of innovative activity, at the midpoint of the S-curve depicted in Figure 1.

The economic historian Carlota Perez argues that financial bubbles and crashes are endogenous to the way in which economies absorb successive technological revolutions (Perez et al., 2010). The dot-com bubble was one of a series of financial booms and crashes that accompanied other innovative industries before the Web. Cases of over-investment followed by a crash occurred during the tulip cultivation mania of 1637, the railway euphoria of the 1840s and the promise of automobiles, oil and petrochemicals in the run up to 1929 (Perez et al., 2010). In every case, the collapse of such bubbles happened midway along the growth path of the technological revolution, at the inflection point of the S-curve.

It seems plausible that the economic bubble leading up to 2000 was linked to the arrival of Web technology (Atkinson et al., 2010; O'Reilly, 2007; Perez et al., 2010). However, to our knowledge, no study has analyzed this assumption quantitatively. If technological advances on the Web were involved in precipitating market movements, we might expect a positive temporal association between Web-related innovation rates and stock market valuations.

2.3. Patents as signals of innovation

Although widely used, *innovation* is an elusive concept that is difficult to define and measure systematically (Erwin & Krakauer, 2004). Measurable parameters of innovation are especially difficult to identify in Web technology, due to its culture of reuse and few centralized systems of formal documentation. We therefore follow previous efforts to overcome the ambiguities of innovation measurement by using patent records (Jaffe & Trajtenberg, 2002). Patents have strict novelty requirements and commercial intent, making them good signals of innovation in technology industries (Andersen, 1999; Haupt et al., 2007; Nicholas, 2008; Useche, 2014; Youn et al., 2015).

Patents offer high quality data including descriptions of each invention, application dates and technical classification codes. This documentation is managed by national government agencies who ensure the reliability and consistency of patent data over an unusually long time span, as well as supporting the accessibility of such data to researchers.

Despite their benefits and convenience, we recognise that patents are a controversial data source. Not all inventions are patented, meaning that patents are limited in the extent to which they represent innovation within industries (Basberg, 1987). This issue is particularly pertinent to Web technology - a fast paced software industry where inventions can be rendered obsolete before a patent is granted (Orsenigo & Sterzi, 2010). Moreover, by preventing imitation, patents inhibit sequential and complementary inventions that utilize an existing piece of software (Dosi et al., 2006). This hampers aggregate information production and puts patenting at odds with the open innovation practices that are valued in software development (Benkler, 2002; Von Hippel, 2005).

Unlike patented inventions, open source strategies benefit from their exposure to a diverse community of developers who have the capacity to test, improve, and maintain software on a large scale (Benkler, 2002). This is reflected in the growth of open source software such as Apache Web server, Python and open Web protocols, whose diffusion and vast applications have exceeded that of equivalent commercial products. However, it is important to acknowledge that the Web is a place where divergent forms of innovation coexist. Firms are able to take advantage of open developments and use them to generate commercial inventions that are protected by intellectual property rights. For example, the W3C consortium eschews patents from Web standardisation activities (Weitzner, 2004), yet some of the leading industry members in W3C such as Facebook, Google and IBM utilise open Web standards in their patented inventions. Web patents therefore sit in an interesting tension point between open and closed innovation systems.

Publicly traded companies operate under commercial pressures that influence the articulation of their innovative value propositions to investors. Especially the years preceding the Initial Public Offering (IPO) are a time when immaterial gestures may be used by commercially driven ventures to heighten the visibility of their technological advances, as exemplified by the "precorporate" era of Facebook (Elmer, 2017). This is a sphere where strategic patents can add a certification value that signals the innovative experience and expertise of new software firms to their prospective investors. Empirical evidence confirms that software patents increase the amount of money collected at IPOs (Useche, 2014).

Other incentives for patent use during the history of the Web relate to institutional changes and market regulation. The boom in Web and Internet-related companies during the 1990s occurred against a backdrop of significant reforms in the US patent system, which was being extended into software and business methods (Wagner & Cockburn, 2010). There was also the "NASDAQ regulation (1984) which allowed market entry and listing of firms operating at a deficit on the condition that they had considerable intangible capital composed of IPR [intellectual property rights]"(Dosi et al., 2006). Such regulations enabled IPR requirements to lower the standards for market entry, precipitating a wave of financially under-performing firms on the NASDAQ during the 1990s (Klein & Mohanram, 2004). This indicates that patents played a significant role in driving industry dynamics in Internet software (Wagner & Cockburn, 2010). Indeed, we find that major commercial inventions in Web technology, such as the Web cookie, PageRank and one-click buying, have been patented.

Although patents introduce limitations to the scope in which we explore innovation on the Web, they capture a worthwhile piece of the Web's commercial history. Moreover, there is substantial benefit and practicality in using patents as a data source. Stringent procedures for the preservation, classification, and dissemination of patent data ensure a reliable, if imperfect, signal of innovation. Unlike other digital archives, patents are less vulnerable to loss or intentional removal. Centralised patent stores enable automated data retrieval approaches that are minimally influenced by human selection bias. The value of such high quality data is nontrivial at a time when researchers endeavour to reconstruct historiographic material about the Web (Brügger, 2013).

3. Methodology

The procedure for gathering Web-related patents is described in Section 3.1. The quality of this dataset was verified using an information retrieval approach outlined in Section 3.2. To examine the shape of technological growth in the Web, the accumulation of patents was modelled using regressions described in Section 3.3. Techniques for detecting associations between Web patents and stock market movements are discussed in Section 3.4. Our patent dataset and analysis scripts are openly available online (Priestley et al., 2020).

Computational operations related to the acquisition and processing of data were implemented in Python version 3.5. Analyses and graphical representations were produced in R version 3.3.2.

3.1. Patent data collection

We used the PatentsView online platform to download a dataset of all US patents[2]. We then identified patents related specifically to the Web using a keyword filtering algorithm on patents filed after 1989. This start date was used because it marks the year when Tim Berners-Lee wrote the first proposal for the Web (Berners-Lee, 1999). The end date of our study was truncated by patent processing considerations. Once a patent application is filed, the pendency period can last over 3 years, meaning that the latest patent grant data are incomplete. To prevent this from skewing our results, we stopped our analysis at 2013. This gave sufficient time for successful patent applications to be granted by the time of our data retrieval in 2018.

Our list of Web-related keywords was informed by operational descriptions of Web technology. To capture the general Web context, we included common words such as "website" and "browser". Additionally, we utilized references to specific technical infrastructures, software, data formats and protocols. These terms were sourced from a comprehensive overview of Web technology (Alonso et al., 2004), canonical descriptions of Web 2.0 (O'Reilly, 2007) and semantic Web applications (Shadbolt et al., 2006), as well as selected W3C and Internet Engineering Task Force (IETF) documents. The full list of keywords is presented in Table 1.

Table 1. Web-related keywords used in the patent filtering procedure.

Web architecture:	Web of services:	Presentation standards:
• HTTP	• CGI	• (X|D)HTML
• HTTPS	• WSDL	• (X)HTML5
• WebSocket	• UDDI	• CSS
• WebDAV	• Servlet(s)	• JavaScript
• URL(s)	• Applet(s)	• DOM
• URI(s)	• SOAP	• XML
• Hypertext | Hyperlink(s) | Hypermedia	• REST	• V(oice)XML
• Browser(s)	• WebRTC	• SISR
• Internet | TCP/IP | Online | Server(s)	• P3P	• SRGS
	• WCAG	• SMIL
Content publishing:		• XSL(T)
• Web(site(s))	*Semantic Web/Web of data:*	• XPath
• Wiki(s)	• RDF(S)	• XQuery
• Blog*	• SPARQL	• XForms
• RSS	• OWL	• JSON
	• SKOS	• SVG
Mobile Web:	• GRDDL	• PNG
• WAP	• PROV	• SSML
• WML		• MathML
		• AJAX
		• CC/PP

In order to qualify for our sample, a patent's title and/or abstract had to either contain the string "world wide web", or *at least two* keywords relating to the Web as specified in Table 1.

Some of the keywords, such as "HTML" or "website", were strongly relevant, while others, such as "web" or "online", could be considered weak due to having alternative meanings in unrelated contexts. For such cases, the requirement of at least two keyword matches improved the closeness of alignment with Web technology. Our procedure allowed the possibility that one of the two keywords could come from a related technical area, such as the Internet, whilst acknowledging that there are other areas that relate to the Web apart from the Internet.

The keyword filtering procedure was implemented in Python using the regular expression (re) library. For two of the keywords, related to the Internet and hypertext, we ensured that thematically similar words could count as one keyword match only (these are indicated by vertical bars in Table 1). For example, a text containing the words "Internet" or "TCP/IP" or "online" or "server" would produce only one match regardless of how many of these terms are present. This restriction ensured that patents focusing on Internet or hypertext technologies alone would not qualify for our sample unless they contained another keyword confirming their relation to the Web.

Our final dataset included inventions that embody advances in Web technology itself (e.g. the Web cookie), as well as inventions that specialise in other domains but utilise the Web to deliver their function (e.g. commercial systems that use websites or web-enabled devices). We manually checked patent titles and abstracts for relevance and excluded 28 patents that were not related to the Web. The subsequent sample consisted of 20,493 relevant patents spanning from November 1990 through December 2013.

3.2. Evaluation of the patent dataset

Our dataset is part of a larger number of Web technology patents that exist in reality. To consolidate the performance of our data gathering procedure in representing this corpus, we utilize the concepts of "precision" and "recall" from information retrieval literature (Manning et al., 2008).

Precision is a measure of quality which, in our case, refers to the fraction of retrieved patents that are related to the Web. By requiring at least two Web-related keywords in each invention, our algorithm ensured a strong relation to the Web context. Consequently, almost all of the retrieved patents were relevant. The manual inspection of our dataset showed that less than 1% of them were unrelated, giving a precision score of over 99%.

The concept of *recall* refers here to the fraction of patents that have been retrieved from the true corpus of relevant patents. This measure of completeness is difficult to gauge as we do not know how many Web patents exist in total. Such challenges in the estimation of recall are common and have received attention in previous literature (Kanoulas, 2016). We approximated the recall of our patent filtering algorithm using a simple test inspired by the "mark-recapture" technique for establishing the size of an unknown population (Booth, 2010). This involves marking the relevant items in an initial sample and comparing their frequency to the number of relevant items retrieved independently. A random sample of 400 patents was drawn from the Cooperative Patent Classification (CPC) group "H04L", which encompasses inventions related to the transmission of digital information. Each of these patents was checked for relevance to the Web using both human inspection and our keyword filtering algorithm as a comparison. Manual inspection of the sample yielded 21 relevant patents, whereas the computational approach returned 13 relevant patents. Eight relevant patents were not accommodated by the algorithm because they did not provide sufficiently explicit textual evidence of the Web context. Based on these figures, we estimate that our data collection procedure had an approximate recall score of 61.9%, meaning that our dataset represents just over half of the true volume of US patents that relate to the Web.

The high precision and comparatively low recall of our methodology reflect a trade-off relationship, which commonly exists where one aspect of data retrieval is improved at the expense of reducing the other (Manning et al., 2008). The present method prioritized high precision at the expense of recall to ensure a parsimonious sample of strongly relevant patents. Precision is the meaningful parameter for our study of temporal trends, where it is more important to know about relative changes in innovation through time rather than their absolute values. Assuming that the limitations of recall were consistent over time, the temporal trends exhibited by our data should still be valid.

3.3. Fitting the growth curve

A growth trajectory was created by plotting the cumulative frequency of Web-related patents over time. The time series was modelled using regression to examine whether linear, exponential, S-shaped or combinations of S-shaped and linear models best captured the observed growth curve. By focusing on parametric (as opposed to nonparametric) regression, we were able to compare theoretical models of growth and interpret their parameters in the context of Web evolution.

Bearing in mind that there are numerous mathematical models that can give rise to the S-shaped growth pattern, we followed the approach adopted by Andersen (1999) in using a simple logistic model to describe the long-term movements of growing industries. All models were fitted using the nls() function in R, and the self-starting function SSlogis() was used to calculate initial parameters for inclusion in the logistic models. The logistic equation is given here by:

$$\frac{Asym}{1 + \exp\left[\frac{(xmid - input)}{scal}\right]} \tag{1}$$

where *input* is a numeric vector of values at which the model is evaluated, *Asym* represents the asymptote (or ceiling) value, *scal* is a scale coefficient on the input axis and *xmid* is a parameter representing the x axis (time) value at the inflection point of the curve. Note that the curve would be exponential for time values before the inflection point ($x < xmid$).

Visual inspection of the plotted data showed an S-curve which appeared to shift to linear growth some time between the years of 2001 to 2005. To accurately estimate the timing, we used piecewise regression to model combined growth curves. For this, the independent variable (numeric date) was divided into two segments for a logistic followed by a linear curve. The timing of the shift was approximated by running 95 piecewise regressions with breakpoints at dates from 2000-11-01 to 2005-11-01 in 30 day intervals. The best fitting model was selected using Bayesian Information Criterion (BIC) values (Burnham & Anderson, 2003). BIC describes the amount of information lost when a statistical model is applied to empirical data; a model with the lowest criterion is preferred.

3.4. Association with the stock market

To examine association between Web-related patenting rates and stock market movements, several adjustments were made to the data. To control for the effects of overall patenting activity on patent applications in the Web sector, the number of Web patents was expressed as a percentage of the total US patent applications filed each month. These percentages were analysed alongside average monthly valuations from the NASDAQ composite stock index over the same date range as the patent sample[3]. The NASDAQ is heavily weighted towards companies in the information technology sector and it has previously been mentioned as the foremost index affected by the dot-com bubble (Atkinson et al., 2010; Perez et al., 2010). If there was an association between Web-related patenting rates and stock market movements, the NASDAQ would likely reveal it to a greater extent than other stock market indices. Short-term fluctuations in both time-series were smoothed using the loess() function in R to discern long-term trends. Both time series had non-stationary properties which could contribute to spurious correlations if unaddressed. We mitigated the issue by using the econometric technique of first-order differencing (Granger & Newbold, 1974). This produced variables that were deemed stationary by Augmented Dickey-Fuller tests (adf.test()), as well as autocorrelation function (acf()) and partial autocorrelation function (pacf()) plots in R.

Association between adjusted patenting rates in Web technology and the NASDAQ index was detected using the Vector Autoregressive (VAR) approach to modelling time-series (Stock & Watson, 2001). VAR modelling is suitable here because it enables us to explore the dynamic relationship between variables with feedback effects, without requiring a priori assumptions about the causal relations between them. A VAR model itself can indicate the most plausible directions of influence. Each variable is regressed on lagged values of itself as well as past values of the other variable(s) in the system to assess the explanatory power, if any, exerted by each variable on the other variable over time. A simple bivariate VAR model is expressed as:

$$\begin{aligned} Y_t &= \beta_{10} + \beta_{11} Y_{t-1} + \ldots + \beta_{1p} Y_{t-p} + \gamma_{11} X_{t-1} + \ldots + \gamma_{1p} X_{t-p} + u_{1t} \\ X_t &= \beta_{20} + \beta_{21} Y_{t-1} + \ldots + \beta_{2p} Y_{t-p} + \gamma_{21} X_{t-1} + \ldots + \gamma_{2p} X_{t-p} + u_{2t} \end{aligned} \qquad (2)$$

where two variables Y and X are regressed with lag order p, and β and γ are coefficients to be estimated (Hanck et al., 2018). The lag length used in our model (8 months) was determined using BIC values provided by the VARorder() function. In accordance with standard practice in VAR analysis (Stock & Watson, 2001), the results of were interpreted using summary statistics of Granger Causality tests and Impulse Response Function (IRF) plots. These were generated using the vars package in R (Pfaff, 2008). VAR regression coefficients are provided in the Appendix.

4. Results

The cumulative time series of patents is shown in Figure 3. Table 2 specifies the parameters for each model that was tested. BIC values showed that the exponential model was least suited to describing our data; simple linear and logistic models were closer to the true values. The best model appeared to begin with a logistic curve which shifted to linear growth after August 2004, instead of declining asymptotically. This piecewise model had the smallest BIC, meaning that it had the smallest discrepancy from the real growth trend. Noteworthy parameters in this curve included the shift from logistic to linear growth in August 2004, as well as the inflection point of the logistic segment in December 2000.

Association between patenting rates and NASDAQ movements is visualized in Figure 4. Table 3 summarizes the Granger Causality results for the two-variable VAR. Granger Causality tests help to establish the direction of influence between variables (Granger, 1969), where a variable Y can be said to "Granger cause" X if Y contains information that helps to explain the future of X better than information in the past of X alone. Thus, Granger Causality allows us to determine statistically whether lagged values of Y provide information that improves our prediction of X.

The Granger Causality test results in Table 3 show that NASDAQ movements help to predict patenting rates at the 0.05 significance level. A similar result also holds in the reverse, where patenting rate helps to predict NASDAQ movements at the 0.001 significance level. This suggests a two-way feedback between our variables.

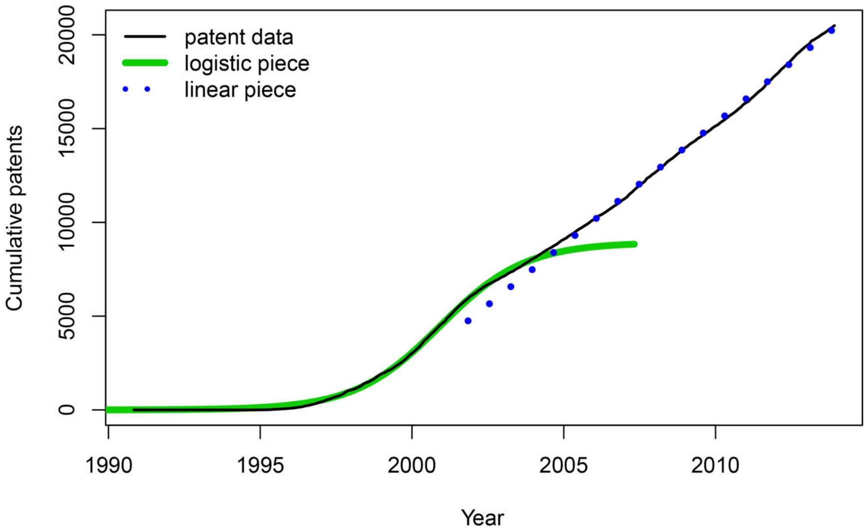

Figure 3. Growth curve of Web-related patents. The data were best fitted by a piecewise model made up of a logistic (thick line) connected to a linear growth curve (dotted line).

Table 2. Model parameters for linear, exponential, logistic and piecewise growth curves. In these regressions, numeric time was the independent variable, measured in days since 1970-01-01; date equivalents are stated in brackets where meaningful.

Linear model:	
Intercept	−24190
Slope	2.66
BIC	4857.66
Exponential model:	
Intercept	4.50
Growth coefficient	0.0003
BIC	4889.42
Logistic model:	
Asymptote	21674.34
Inflection point (date)	13303.48 (2006-06-04)
Growth coefficient	1318.96
BIC	4458.44
Piecewise model:	
Breakpoint (date)	12632 (2004-08-02)
Logistic parameters before breakpoint:	
Asymptote	8928.92
Inflection point (date)	11292.75 (2000-12-01)
Growth coefficient	511.32
Linear parameters after breakpoint:	
Intercept	−36420
Slope	3.54
BIC	3486.25

One of the advantages of VAR modelling is that it enables us to estimate the impact of changes in one variable on the other variable over a period of time. This is done through the use of Impulse Response Function (IRF) plots, which are provided in Figure 5. These plots illustrate the magnitude and direction (positive or negative) of interactions between two variables over time.

Panel A of Figure 5 shows that a 1 point increase in the NASDAQ is associated with a 0.003% percentage point increase in the proportion of Web-related patents after

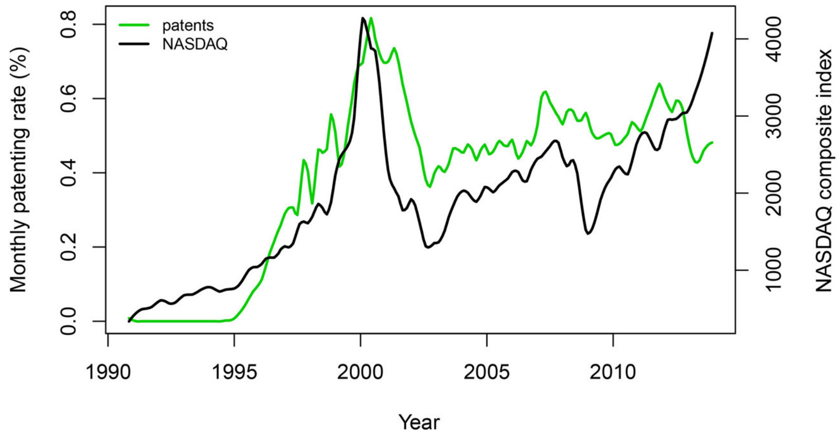

Figure 4. Association between patenting rates and the NASDAQ index. Monthly percentage of Web-related patents (light line) overlaid by NASDAQ composite index values (dark line).

Table 3. Granger Causality test results.

H_0	F	p
NASDAQ does not Granger cause patents	2.23	0.02
Patents do not Granger cause NASDAQ	6.69	0.00

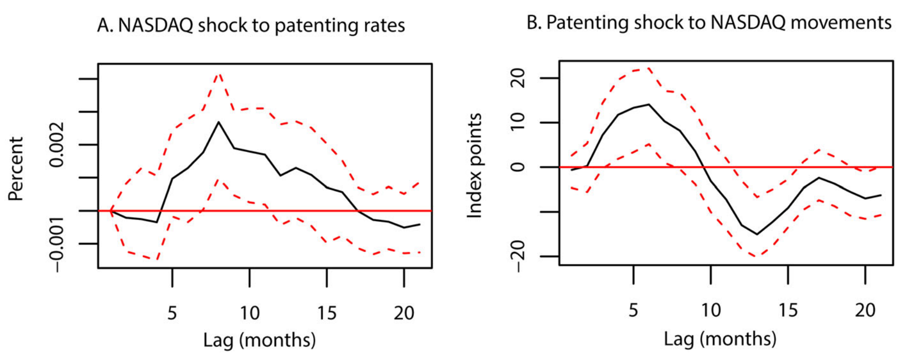

Figure 5. Impulse response function plots. Also plotted are standard error bands and a zero baseline.

8 months. Panel B of Figure 5 shows that a 1 percentage point increase in the proportion of patent applications that relate to the Web is associated with a 14 point increase in the NASDAQ 6 months later and a 15 point decrease in the NASDAQ 13 months later.

5. Discussion

The aim of this article was to draw on literature regarding typical patterns of technological innovation to investigate the long-term development of Web technology in a commercial context. Below we discuss the results of using historical patent data to examine the shape of technological growth in the Web industry and its association with stock market movements.

Our results show that the growth of Web technology patents *began* with an S-shaped pattern which is consistent with typical development in industries. In line with earlier discussions of technology gestation periods (Adner & Levinthal, 2002), there was very little growth in the first few years of the Web. Since its invention in 1989, the Web started out as a relatively obscure technology used by a niche community of academics and technology enthusiasts. It is likely that its steady acceleration between the years of 1995 to 2000 was stimulated by the activities of the W3C. After being founded in 1994, the consortium attracted a membership spanning hundreds of commercial, academic and government organisations (Berners-Lee, 1999). By 1998, this community had created a dozen technical recommendations to support the scale and interoperability of Web applications.

The newly emerging Web architectures opened exciting opportunities for deployment in the commercial sector. A substantial amount of hype was generated in the run-up to 2000 and capital was channeled towards Web-based ventures. This expansion is reflected by the exponential period of growth in our curve, which is found to last until December 2000 based on the inflection point of the S-curve. This means that claims about the exponential growth of the Web may have been reasonable two decades ago (Huberman & Adamic, 1999), but would be less accurate in recent discussions. As the potential of e-businesses had been exaggerated during those early years, investors became more sceptical after the dot-com crash in the spring of 2000 (Wheale & Amin, 2003). The timing of maximum technological growth in our findings coincides rather closely with this change in attitude. Such a result lends support to the idea that inflection points in technological development tend to mark the turning point between phases of prosperity to recession (Kuznets, 1940; Perez et al., 2010).

It must be highlighted that the overall growth curve uncovered here did not decline towards the usual ceiling of the S-curve. Our S-curve of Web technology patents shifted to linear growth after August 2004. Instead of succumbing to the bleak projections of continued decline after the dot-com crash, the Web appears to have sustained a steady level of patent growth over the next decade (Arthur, 2002). It is striking that the timing of the transition to linear growth occurred approximately a year before the term "Web 2.0" was popularised in 2005 (O'Reilly, 2007). This new phase was characterised by social networks, interactivity and collaboration - activities that drew heavily on the culture of interoperability enabled by Web standards that were developed in the earlier decade (Hall & Tiropanis, 2012; Sykora, 2017). It seems plausible that Web standardisation played a foundational role in creating the persistent architectures and protocols that guided the industry into continued incremental growth, where existing technological functionalities could be elaborated and deployed in new application domains and market niches.

The linear growth segment observed in our findings could be composed of a series of successive S-curves that resemble Figure 2 presented earlier in this article. Empirical studies from numerous industries have observed technological improvement past the limits of a single S-curve when a series of new technologies emerge successively (Chang & Baek, 2010; Christensen, 1992; Sood & Tellis, 2005). In the present case, there could be a number of technologies and spin-off applications that contributed to the extension of Web technology at large. Examples include Artificial Intelligence (AI), smartphones and the Internet of Things.

The second aim of our article was to examine whether corporate innovation in Web technology had a historical association with stock market movements. This inquiry was motivated by reports that technological revolutions typically stimulate positive financial speculation among investors (Perez et al., 2010), and the suggestion that the dot-com boom and bust of 2000 was tied to the maturation of the Web industry (Atkinson et al., 2010; O'Reilly, 2007; Perez et al., 2010). In support of these observations, our empirical findings demonstrate a relation between patenting rates in Web technology and movements of the NASDAQ composite stock index. However, this relation was found to be bi-directional and complex.

On the one hand, changes in the NASDAQ were positively associated with changes in patenting activity occurring 8 months later, suggesting that economic incentives were a precedent to research effort and innovation in the Web industry. On the other hand, patenting activity appeared to be linked with an increase in the NASDAQ index 6 months later and a decrease 13 months later, suggesting that the positive influence of innovation diminished over the course of a year. The initial part of this result is consistent with previous findings of patents serving as signals of competence that drive investment activity (Useche, 2014). It seems more surprising, at first glance, to observe that patenting activity was associated with reduced market valuations at a later time. However, such a trend seems logical if we consider the unfulfilled expectations of investors, whose high hopes in the value of innovation may not have materialised as expected. Previous studies found that the positive influence of innovation on investors' decisions declined during periods of recession (Nicholas, 2008; Wheale & Amin, 2003). What this implies for our study is that the perceived value of Web innovation changed over time, perhaps in connection with the life cycle of the stock market boom and bust.

6. Final remarks

Our patent-based study sheds new light on the question of commercial innovation and speculative investment during the evolution of the Web industry in the US. By looking at this particular context from a historical perspective, we highlight a balance between the pervasive and changing aspects of corporate innovation, providing evidence that can inform policy. Below we discuss the implications of our study for managers, academics and entrepreneurs, followed by possible avenues for future work.

1. **Corporate strategy.** For technology management and industry, our results encourage discernment when using the S-curve for theoretical discussions and projections of economic growth in a technology industry. Even when a technology appears to be approaching a ceiling of improvement, analysts and managers could still uncover opportunities to stimulate substantial growth in commercial innovations. In the near future of the Web, we suggest that such growth could arise from data assets, human capital and AI.

2. **Community support.** Our findings suggest that the long-term economic growth in the Web has likely been subject to the extension opportunities granted by other complementary technologies. To capitalise on this, Web and Internet communities must continue building open and interoperable systems that are compatible with external technological advances. Academic fields affiliated with Internet and Web Science add value here by assessing the broader ecosystem of technologies and social structures in which the Web is embedded (Hall et al., 2017).
3. **Challenges and opportunities for financial investment.** Our results imply a bi-directional link between corporate innovation in the Web industry and high-tech investment. On the one hand, financial rewards can incentivise corporate innovation. On the other, corporate innovations can serve as signals that inspire investor confidence, as well as introducing the possibility of subsequent disappointment. Policy makers and entrepreneurs should be aware that the market value of commercial innovations may change with the economic climate. Periods of hype should also remind investors to be more moderate in their decisions.

There are a number of limitations in this study. Firstly, our reliance on patents as an indicator of innovation is meaningful in a very specific commercial context that may not necessarily generalise to a broader understanding of the Web's history. Patents capture a small subset of corporate innovation occurring in industries. We cannot eliminate the possibility that the observed trends were an artefact of our data selection procedure. Another drawback is that the composition of companies in the NASDAQ is not identical to those who filed patent applications related to the Web, meaning that the association observed in our study could be attributable to other variables that were not explicitly modelled. Despite these limitations, we are confident that the basic result of this article is meaningful and at least crudely captures the association between corporate Web innovation and major stock market movements at an aggregate level of analysis. By using quantitative analysis on a piece of the Web's commercial history, our study makes a novel addition to other spheres of public and civic interest addressed by previous Web archiving and history studies.

The peculiarities in our findings indicate avenues for future work. First, it would be useful to examine empirically the specific emerging technologies that contributed to the growth of Web technology patents after 2004. It would also be useful to further explore the possible influence of patenting rates on the NASDAQ index. The nature of the relationship between these variables could have changed in magnitude and direction throughout the 23 year window of our investigation. Distinguishing between different time segments and phases of economic development could therefore be a promising undertaking for future research.

Notes

1. For European patents, bulk data retrieval is restricted by fees.
2. Bulk patent data were sourced from http://www.patentsview.org/download/.
3. NASDAQ data were downloaded from https://fred.stlouisfed.org/series/NASDAQCOM

Acknowledgements

We would like to thank the anonymous reviewers for their insightful suggestions which improved the quality of this article. We are also grateful to Alex Mesoudi, Vadim Grinevich, Les Carr, Alexander Brem, Carsten Bergenholtz and Valentina Fani for their useful comments on earlier versions of this work. Other helpful feedback was received when our preliminary results were presented at the Breaking Silos Conference (Southampton, 2018) and the DRUID Academy Conference (Odense, 2018). Any errors or omissions are our own.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

This work was funded by the Digital Economy programme, led by the Engineering and Physical Sciences Research Council on behalf of UK Research and Innovation. Grant number EP/L016117/1.

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Appendix A. VAR regression coefficients

In the Tables A1 and A2, Patents and NASDAQ refer to adjusted time-series variables that underwent smoothing and differencing prior to inclusion in the VAR.

Table A1. VAR equation results for Patents.

Variable	Coefficient	*t* statistic	*p*
Constant	3.95×10^{-4}	0.70	0.49
$Patents_{t-1}$	1.14	18.80	0.00
$Patents_{t-2}$	-6.24×10^{-1}	−6.73	0.00
$Patents_{t-3}$	3.59×10^{-1}	3.56	0.00
$Patents_{t-4}$	-5.55×10^{-1}	−5.55	0.00
$Patents_{t-5}$	4.42×10^{-1}	4.46	0.00
$Patents_{t-6}$	-1.82×10^{-1}	−1.82	0.07
$Patents_{t-7}$	2.57×10^{-1}	2.71	0.01
$Patents_{t-8}$	-2.72×10^{-1}	−4.30	0.00
$NASDAQ_{t-1}$	-9.08×10^{-6}	−0.38	0.71
$NASDAQ_{t-2}$	1.15×10^{-5}	−0.28	0.78
$NASDAQ_{t-3}$	-1.05×10^{-5}	−0.25	0.80
$NASDAQ_{t-4}$	6.71×10^{-5}	1.79	0.07
$NASDAQ_{t-5}$	-8.67×10^{-5}	−2.28	0.02
$NASDAQ_{t-6}$	7.15×10^{-5}	1.71	0.09
$NASDAQ_{t-7}$	-2.38×10^{-5}	−0.59	0.55
$NASDAQ_{t-8}$	1.22×10^{-5}	0.52	0.60

adj. $R_2 = 0.72$.

Table A2. VAR equation results for NASDAQ.

Variable	Coefficient	*t* statistic	*p*
Constant	2.14	1.48	0.14
$NASDAQ_{t-1}$	1.34	21.93	0.00
$NASDAQ_{t-2}$	-3.45×10^{-1}	−3.32	0.00
$NASDAQ_{t-3}$	8.52×10^{-2}	0.81	0.42
$NASDAQ_{t-4}$	-7.92×10^{-1}	−8.33	0.00
$NASDAQ_{t-5}$	7.01×10^{-1}	7.25	0.00
$NASDAQ_{t-6}$	-8.97×10^{-3}	−0.09	0.93
$NASDAQ_{t-7}$	-2.04×10^{-2}	−0.20	0.84
$NASDAQ_{t-8}$	-1.20×10^{-1}	−2.03	0.04
$Patents_{t-1}$	$1.19 \times 10^{+2}$	0.77	0.44
$Patents_{t-2}$	$6.01 \times 10^{+2}$	2.56	0.01
$Patents_{t-3}$	$-5.20 \times 10^{+2}$	−2.03	0.04
$Patents_{t-4}$	$8.99 \times 10^{+1}$	0.35	0.72
$Patents_{t-5}$	$4.78 \times 10^{+1}$	0.19	0.85
$Patents_{t-6}$	$2.71 \times 10^{+2}$	1.06	0.29
$Patents_{t-7}$	$4.05 \times 10^{+1}$	0.17	0.87
$Patents_{t-8}$	$-6.20 \times 10^{+2}$	−3.86	0.00

adj. $R_2 = 0.92$.