

Financial Disruptions and the Organization of Innovation: Evidence from the Great Depression

Tania Babina

Columbia University, USA

Asaf Bernstein

Leeds School of Business, University of Colorado at Boulder
and NBER, USA

Filippo Mezzanotti

Kellogg School of Management, Northwestern University, USA

We examine innovation following the Great Depression using data on a century's worth of U.S. patents and a difference-in-differences design that exploits regional variation in the crisis severity. Harder-hit areas experienced large and persistent declines in independent patenting, mostly reflecting the disruption in access to finance during the crisis. This decline was larger for young and inexperienced inventors and lower-quality patents. In contrast, innovation by large firms increased, especially among young and inexperienced inventors. Overall, the Great Depression contributed to the decline in technological entrepreneurship and accelerated the shift of innovation into larger firms. (*JEL* G01, G21, O3, N12, N22, N32)

Received November 30, 2020; editorial decision October 12, 2022 by Editor Holger Mueller. Authors have furnished an Internet Appendix, which is available on the Oxford University Press Web site next to the link to the final published paper online.

This paper builds on an earlier version of the project titled "Crisis Innovation." We would like to thank Brian Beach, Shai Bernstein, Charles Calomiris, Bill Collins, Pranav Desai, Katherine Eriksson, James Feigenbaum, Michela Giorcelli, James Fenske, Alex Field, Walker Hanlon, Christian Helmers, Taylor Jaworski, Chad Jones, Pete Klenow, Naomi Lamoreaux, Yueran Ma, Gustavo Manso, Kris Mitchener, Petra Moser, Ramana Nanda, Tom Nicholas, Santiago Perez, Bitsy Perlman, Sarah Quincy, Gordon Phillips, Tom Schmitz, Amit Seru, Chenxi Xu, Ting Xu, and Nicolas Ziebarth, Ariell Zimran and seminar participants at the Amsterdam Business School, Auburn University, University of Colorado at Boulder, Columbia Business School, Hass School of Business, the 2022 AFA, the 2019 HEC Workshop on Entrepreneurship, the HKUST finance seminar, the IMF Annual Macro-Financial Research Conference, Michigan State University, 2019 Minnesota Junior Finance Conference, 2019 Labor and Finance Group, Northwestern University Economic History Festival, 2020 NBER SIDA, EFA, Owen Graduate School of Management, Rutgers University, Stanford University, the Tuck School of Business, the 2019 UT Dallas Finance Conference, the University of Virginia, the Third Junior Entrepreneurial Finance and Innovation Workshop, WFA, the 2020 Workshop on Entrepreneurial Finance and Innovation, FIRS 2021, the Barcelona Forum 2021, the WEFI, and the 2020 Virtual Economic History Seminar. All errors are our own. Belinda Chen, Nicholas Jeanrenaud, Tam Mai, and Ayush Sinha provided outstanding research assistance. [Supplementary](#) data can be found on *The Review of Financial Studies* web site. Send correspondence to Filippo Mezzanotti, filippo.mezzanotti@kellogg.northwestern.edu.

The Review of Financial Studies 36 (2023) 4271–4317

© The Author(s) 2023. Published by Oxford University Press on behalf of The Society for Financial Studies. All rights reserved. For permissions, please e-mail: journals.permissions@oup.com.

<https://doi.org/10.1093/rfs/hhad023>

Advance Access publication April 3, 2023

How economic crises, in particular when connected with a large financial disruption, affect innovation is an unsettled and important question for economic growth. In this paper, we examine patenting activity in the aftermath of the Great Depression to understand whether this crisis played an important role in reshaping innovation activity. By their own nature, crises are deeper and more protracted than typical business cycle fluctuations, making negative fallouts potentially large and persistent (Cerra and Saxena 2008), especially when these events are accompanied by a reduction in the ability of capital providers to fund productive opportunities (Bernanke 1983). Consequently, these shocks can directly disrupt the process of producing innovation, potentially resulting in important setbacks in economic activity (Hall 2015; Gourio, Messer, and Siemer 2016). However, such events may also create a window of opportunity to reorganize the innovation process toward more efficient organizational forms, potentially accelerating the processes of structural transformation already in place in the economy (Schumpeter 1942; Manso, Balsmeier, and Fleming 2019).

Our key contribution is to show that the unfolding of the Great Depression led to a persistent decline in innovation by technological entrepreneurs and accelerated the shift of innovation into larger firms. Using new comprehensive data on U.S. innovation spanning more than a century, we document that areas harder-hit by the Great Depression experienced a large and persistent decline in patenting by independent inventors which lasted for the next 70 years. This category of innovators produced inventions outside the boundaries of a traditional firm, much like modern technological entrepreneurs. The decline was larger for younger and less experienced inventors, and it appears to largely reflect the disruption to access to capital induced by the crisis in the local market. However, we also find that this decline was partially compensated by a rise in patenting by large firms, and this increase is in part driven by the same categories of inventors (i.e., young and inexperienced) that were more affected when operating as independent inventors. Lastly, the long-run decline for independent inventors was more pronounced in technology areas characterized by a greater competitive advantage for firms in raising capital and managing complex technologies. Overall, these findings are consistent with the Great Depression acting's as a catalyst for a significant transformation in the way innovation was organized, and, in particular, it accelerated the demise of technological entrepreneurs to the advantage of larger firms.

Our work contributes to the existing literature in several ways. First, despite the large literature studying the effects of the Great Depression, much less is known about its impact on innovation, especially outside of firm boundaries. This dimension was particularly important during the Great Depression. Prior to the 1930s, innovation produced by independent inventors was the predominant form of patenting (Lamoreaux, Sokoloff, and Sutthiphisal 2009); however, to the best of our knowledge, no comprehensive study exists that explores how this important inventor group fared in the aftermath of the

Great Depression. Second, while most studies examine innovation by focusing on either incumbents or entrants separately, our new comprehensive patent data allow us to show the dynamic connection between innovation by both technological entrepreneurs and incumbent firms in response to a crisis. Third, we document how different types of inventors fared in the face of the crisis. This analysis can provide novel insights about the distributional impact of a crisis; this dimension is usually difficult to examine in recent periods because of the lack of data on the characteristics of inventors. Finally, our work is one of the first to examine the role of a crisis in shaping innovation over a very long period, by measuring subsequent changes in patenting for almost a century.

To examine these questions, we use two main data sets. First, we exploit historical patent data spanning more than a century to construct different measures of county-level innovation. In particular, on top of observing firm patenting in a county, we develop and validate a novel measure of technological entrepreneurship based on independent patenting, that is, innovation produced outside the boundaries of a firm. These data enable us to study the drivers of entrepreneurship for a time when data were not previously available by measuring how the entire local innovation ecosystem responded to the crisis and observing its long-run effects. We construct a second key data set that consists of longitudinal inventor-level data that link inventors who patented between 1905 and 1945 across four decennial full-count U.S. censuses. These new data allow us to measure how different types of inventors were affected by the Great Depression.

To identify the effects of the Great Depression, we use a difference-in-differences design that exploits county-level variation in acuteness of the Great Depression. For our primary specifications, we use bank suspensions as a proxy for the local severity of the crisis, given the central role of bank distress in studies of crises more generally (Reinhart and Rogoff 2009) and the Great Depression in particular (Bernanke 1983; Gorton, Laarits, and Muir 2019; Mitchener and Richardson 2019). Our interpretation is that this measure largely captures a specific aspect of the crisis, namely, disruption in access to finance.¹ Consistent with this hypothesis, we provide evidence based on quantitative analyses and historical accounts that highlight the deteriorating financing environment during the 1930s as an important factor in our findings. For instance, we find similar results when we use other measures of the crisis severity that proxy for the disruption to local capital, but not when we use measures of broader economic contraction (e.g., the decline in retail sales and unemployment). However, we also recognize that disentangling the specific channel by which the Great Depression affects innovation is difficult because proxies for different channels tend to be indirect, and economic

¹ However, our approach does not necessarily aim to recover the causal effects of bank suspensions specifically, since banks did not play a significant direct role in financing technological entrepreneurs.

and financial aspects were tightly linked during the Great Depression. In light of this discussion, the main threats to identification come from the presence of alternative economic forces (e.g., differences in the regulatory environment) that would have driven variation in bank suspensions and innovation, even in the absence of the Great Depression. While we undertake a number of robustness tests throughout the paper to address these concerns, our specifications always include state-by-time fixed effects to flexibly control for state-level confounding factors and county fixed effects to control for unobserved time-invariant heterogeneity across counties.

Using this design, we document that local disruptions from the crisis predict a sudden and substantial decline in patenting by technological entrepreneurs. For instance, areas harder-hit by the Great Depression saw a 13% greater decline in patenting by independent inventors in the immediate aftermath of the crisis. This decline was persistent, lasting every decade for the next 70 years. The drop in independent innovation is mainly driven by inventors who self-identified as entrepreneurs in the census, suggesting that the decline captures a real reduction in entrepreneurial activity. Parallel trends prior to the shock, evidence of a drop within every major technology class, and similar results using alternative shocks all suggest that the effects are driven by local shocks due the Great Depression. We have two key findings on the distributional impact of the economic crisis on different groups of inventors. First, the declines are especially large for young and inexperienced independent inventors who might have been less resilient in the face of such shocks: these inventors were less likely to have social, reputational, or financial capital to buffer the crisis and therefore, were less likely to have been able to innovate on their own in the aftermath of the crisis. Second, the drop in independent inventions is larger among lower-quality patents, consistent with the evidence on cleansing effects during crises (Caballero and Hammour 1994).

This large decline in independent innovation suggests that the fallout from the Great Depression may have facilitated the ongoing transition of U.S. innovation away from entrepreneurs and toward large firms (Lamoreaux, Sokoloff, and Sutthiphisal 2009; Nicholas 2010). Our additional sets of results focusing on firm innovation support this interpretation. We find that distressed areas saw a relative increase in patenting by large, incumbent firms. This increase is greater among the same kinds of inventors who suffered the largest declines in patenting independently (i.e., the young and inexperienced). These findings suggest a tight connection between the decline in independent inventors and the rise of patenting by large firms. In contrast, just like independent inventors, new firms experienced a decline in patenting in more-distressed areas. Furthermore, in the long run, large firms' patents increased not only in number but also in the overall quality of their output, as measured by total citations. These results suggest that, in the long run, larger firms may have, in part, benefited from this transition. The lack of relative decline in innovation by large incumbent firms in more distressed areas is

broadly consistent with financial disruptions playing a significant role in this setting, but could certainly also reflect more general resilience of these entities in face of a crisis.

Even though the crisis eventually passed, its effects on innovation appear to be long-lived. We argue that this persistence may be explained by the Great Depression's acting as a catalyst in accelerating the (ongoing) transition of U.S. innovation from being entrepreneur-centric—where independent inventors are at the center of the innovation process—to more firm-centric. The transition between different organizational forms of innovation is complicated because of the presence of externalities that may generate hysteresis (Aghion and Tirole 1994; Gromb and Scharfstein 2002; Hellmann 2007; Ding and MacKay 2017). Hence, while in aggregate, firm innovation may have been already gaining a competitive advantage relative to independent inventors, the actual transition could take a long time to materialize. In this context, a deep economic crisis could lead to a dissolution of important aspects of the local ecosystems and, therefore, facilitate the transition between possible equilibria. For example, a large contraction in risky capital can severely damage important aspects of the local entrepreneurial ecosystem and this disruption may persistently affect the ability of local technological entrepreneurs to raise funds. Consistent with this narrative, those independent inventors that are more likely to be subject to these information asymmetries and suffer from the disruption of local networks (i.e., younger and/or less experienced inventors) see larger declines.

Furthermore, we also find that the long-term decline in independent innovation was greater where the incentive to shift innovation into firms was greater. Following the literature, we argue that the increase in firms' comparative advantage in innovation can be explained in part by their superior ability to raise large pools of capital and manage evermore complex technologies (Teece David 1988; Hughes 2004; Lamoreaux and Sokoloff 2005). Indeed, we find that the long-run decline in independent patents is larger along these dimensions. First, the decline in independent patenting is larger for technologies used in industries that are more dependent on external financing. This result is also consistent with the general interpretation of our results as reflecting, at least in part, a shock to local financing. Second, independent patents decline more for those inventors who are unable to successfully manage complex technologies and operate in teams and, consequently are unable to compete effectively with firms in this dimension. In contrast, we find no evidence that the persistence of the decline in independent patents in distressed areas is related to an increase of government involvement in innovation in the post-depression era or explained by an increase in inventor out-migration. Overall, despite a multitude of explanations, the evidence supports the idea that the Great Depression—at least partially by impairing capital access and disrupting the local ecosystem in which technological entrepreneurs operated—accelerated the transition of innovation into larger

firms. This includes our findings that the largest declines in patenting are by independent inventors in counties with proxies more closely associated with financial-related disruptions, among young inexperienced and solo inventors, and in technologies used in industries more dependent on external financing, while relative increases occur among large incumbent firms.

1. Related Literature

This paper contributes to several strands of literature. First, our findings speak to the literature on the economic impact of the Great Depression. While much has been written on the consequences of this crisis on economic growth, prices, employment, and other real outcomes, much less is known about its impact on innovation, especially outside of firm boundaries.² Indeed, this dimension was particularly important during the Great Depression: prior to the 1930s, innovation produced by independent inventors was the predominant form of patenting. For instance, [Nicholas \(2010\)](#) shows that in the 1920s, around 70% of all U.S. patents were attributed to independent inventors. At the same time, independent inventors were also important from a qualitative standpoint. Historically, some of the most impactful inventions were initially developed by independent inventors and the ex post quality of their innovation output is on average higher than firms' innovation during the same period ([Lamoreaux, Sokoloff, and Sutthiphisal 2009](#); [Nicholas 2010](#)).³ To the best of our knowledge, ours is the first comprehensive study on how this important inventor group fared in the aftermath of the Great Depression as well as how it shaped the organization of innovation. We complement the literature that focuses on how the unfolding of the Great Depression affected established businesses by documenting that it led to a persistent decline in technological entrepreneurship and accelerated the process of shifting innovation into larger firms.⁴

² Economists have typically focused, among other things, on the effects of monetary policy ([Friedman and Schwartz 1963](#); [Richardson and Troost 2009](#); [Gorton and Metrick 2013](#)), demand declines ([Temin 1976](#); [Romer 1993](#)), international flows ([Eichengreen 2004](#)), shocks to productivity ([Cole and Ohanian 2007](#)), government policy response ([Fishback, Horrace, and Kantor 2001](#); [Fishback, Kantor, and Wallis 2003](#)), economic growth ([Gordon 1999](#)), bank lending amplifiers ([Bernanke 1983](#); [Gorton, Laarits, and Muir 2019](#); [Mitchener and Richardson 2019](#); [Mitchener and Richardson 2020](#)), and bank distress specifically ([Calomiris and Mason 2003](#)).

³ To be more precise, both [Lamoreaux, Sokoloff, and Sutthiphisal \(2009\)](#) and [Nicholas \(2010\)](#) find that over the 1900–1929 period, independent patents were, on average, of higher quality than firm patents, as measured by future citations and the number of claims in the patent text. For example, using a random sample of patents filed over 1928–1929, [Lamoreaux, Sokoloff, and Sutthiphisal \(2009\)](#) show that 36% of the independent patents were cited by patents filed over 1975–2000 in the NBER patent data, which is higher than for patents filed by firms with R&D laboratories (25%–30%). This evidence is consistent with the results in [Kelly et al. \(2018\)](#), that show that independent inventors represented a substantial share of breakthrough patents in the first half of the twentieth century.

⁴ For instance, recent empirical work has documented large negative effects of the Great Depression on business revenues ([Ziebarth 2013](#)), business failures ([Babina, Garcia, and Tate 2017](#)), and employment ([Benmelech, Frydman, and Papanikolaou 2019](#); [Lee and Mezzanotti 2017](#)).

Within the context of the Great Depression, our results also help to reconcile seemingly contradictory findings of the destructive nature of the Great Depression and the evidence in [Field \(2003\)](#) that describes the aftermath of the Great Depression as an era of incredible technological progress and innovation. While we find that the unfolding of the Great Depression led to a contraction in patent filings by technological entrepreneurs, we also show that large firms increased patenting, especially in areas in which independent inventor activity contracted more, and their overall innovation quality rose. These findings suggest that large firms hired inventors who no longer could invent on their own and benefited from the fruits of their ingenuity. Moreover, our evidence on cross-organizational migration suggests that reallocative forces are critical to understanding the full response of innovation to the crisis.

Our evidence is also relevant in the context of the growing literature studying how innovation is affected by periods of crisis. While most past work focuses on the impact on incumbent firms or startups separately, our new comprehensive patent data allow us to show the dynamic connection between innovation by technological entrepreneurs and incumbent firms in response to a crisis. More broadly, our evidence highlights how the impact of a crisis is not uniformly negative. In fact, although innovation by technological entrepreneurs was severely affected, the reduction was mostly concentrated among lower-quality inventions, and the shock also propelled the reallocation of innovation into larger firms, which in part may have limited the economic costs of the crisis. This evidence is consistent with previous theoretical evidence. For instance, [Manso, Balsmeier, and Fleming \(2019\)](#) builds a model and estimates that economic downturns can trigger more exploratory and novel innovations, while [Inderst and Muller \(2004\)](#) find increased screening of startups by capital providers during downturns.⁵ In this area, our paper also complements work by [Nanda and Nicholas \(2014\)](#), which focuses on firms that own R&D labs and shows that the negative effect of the Great Depression on those firms was relatively limited and mostly concentrated in industries highly dependent on external finance. Importantly, the idea that economic crises are not inherently bad is not new to the contemporary debate. For instance, [Schumpeter \(1934\)](#) considers the costs of a major fallout in economic activity in the aftermath of the Great Depression, and also concludes that “depressions are not simply evils, which we might attempt to suppress, but—perhaps undesirable—forms of something which has to be done, namely, adjustment to previous economic change.”

⁵ This is also consistent with evidence that highlights how these large shocks may increase productivity by improving the allocation of capital and labor ([Bai, Carvalho, and Phillips 2018](#); [Caballero and Hammour 1994](#)). However, recent papers also find potentially negative effects of large economic shocks on productivity and innovation by some incumbent firms (e.g., [Duval, Hong, and Timmer 2020](#); [Bernstein, McQuade, and Townsend 2021](#)), and, hence, more work is needed to understand when productivity and innovation suffer and when they improve in response to a severe economic shock.

Our results also contribute to our understanding of the determinants of innovation and its organization.⁶ Although modern patenting is dominated by firms, this organizational structure of innovation is neither historically ubiquitous (Nicholas 2010; Kenney 2011; Landes, Mokyr, and Baumol 2012) nor clearly theoretically dominant (Aghion and Tirole 1994; Gromb and Scharfstein 2002), and holdup problems and the stage of innovation affects the decision to innovate within firms (Frésard, Hoberg, and Phillips 2020). Within this context, our paper highlights how a period of economic crunch—by leading to the dissolution of important aspects of the status quo—may facilitate structural changes in the way innovation is organized. We show that the Great Depression interacted with underlying technology forces that were already improving the competitive position of large firms relative to independent inventors (Teece David 1988; Hughes 2004; Lamoreaux and Sokoloff 2005; Arora et al. 2021) and contributed to the shift of U.S. innovation from being entrepreneur-centric to more firm-centric.

Our paper also contributes to the literature on entrepreneurship and, more generally, on research on the boundaries of the firm (e.g., Coase 1937; Hart 1988). Specifically, several papers examine the role of established firms in “entrepreneurial spawning”: the drivers of departures of firm employees to start new ventures. For example, Gompers, Lerner, and Scharfstein (2005) find that firms backed by venture capital and nondiversified incumbent firms spawn more startups, and Nanda and Sørensen (2010) find that firms with more workers with prior entrepreneurial experience spawn more new entrepreneurs. Firms’ choice of corporate financial policies is also important in driving employee departures to start new firms. For example, incumbent firms that become financially distressed lose talent to startups (e.g., Babina 2020).⁷ We contribute to this literature in two ways. First, much less is known about the other way around: which factors determine when entrepreneurs return to work for incumbent firms or explain whether newcomers to the job market are more likely to pursue entrepreneurship or get paid jobs.⁸ Our findings suggest that a period of financial disruptions can make it less feasible for more vulnerable

⁶ While a complete review is beyond the scope of this paper, these determinants include the role of immigration (e.g., Kerr and Lincoln 2010; Moser, Voena, and Waldinger 2014), taxation (e.g., Akcigit, Grigsby, and Nicholas 2017), intellectual property laws and enforcement (e.g., Moser 2005; Mezzanotti 2020), government investments in R&D (e.g., Gross and Sampat 2020; Moretti, Steinwender, and Van Reenen 2019), bank credit (e.g., Bai, Carvalho, and Phillips 2018; Huber 2018), boundaries of the firm (e.g., Seru 2014; Frésard, Hoberg, and Phillips 2020), competition (e.g., Aghion et al. 2005), and exposure to innovation (e.g., Bell et al. 2019), among other things.

⁷ Firms also lose many employees to entrepreneurship when they go public (Babina, Ouimet, and Zarutskie 2020), likely because employees are able to cash out their equity ownership following the IPO or ramp up spending on corporate R&D (Babina and Howell 2018), consistent with R&Ds generating ideas that the investing firms pass on because these ideas are far from the firm’s focus.

⁸ Recent work has shown that the COVID-19 crisis led to the decline of labor supply to startups (Bernstein, Townsend, and Xu 2020) and that when university researchers experience severe cuts to their federal R&D funding, they are much less likely to commercialize their research in high-tech startups (Babina et al. 2020b).

groups of (prospective) entrepreneurs, such as younger and more inexperienced people, to innovate on their own, but that some of this talent can still innovate while working for larger firms. Second, to the best of our knowledge, prior to this work, there has been no comprehensive U.S. data for the time before the 1980s that would allow one to measure entrepreneurial activity in a comprehensive and consistent way. We build a comprehensive and validated data on technological entrepreneurship spanning almost two centuries.

2. Historical and Institutional Background

2.1 The organization of innovation in the early twentieth century

In the early twentieth century, U.S. innovation, in large part, occurred within two main organizational forms: firms (often with R&D laboratories) and independent inventors. While the boundaries between these two types of organizations may have been blurry along some dimensions, they also clearly differed along several dimensions.

First, they financed themselves differently. In general, independent inventors rarely used direct bank financing. Instead, they financed their inventions either by using personal resources or by raising equity financing from local wealthy individuals who played a role similar to modern angel investors (Lamoreaux, Sokoloff, and Sutthiphisal 2009; Nicholas 2010). Hence, the vitality of local entrepreneurial ecosystems partly depended on the fortunes and risk appetite of its wealthy residents.⁹ In contrast, the financing of innovation by established firms was less dependent on the local network of investors. Similar to most modern corporations, it is generally accepted that a large part of established firms' R&D investment was covered by internally generated cash flows (Hall and Lerner 2010). At the same time, firms raised funding through a variety of mechanisms, such as the sale of equity securities (Nicholas 2008; Lamoreaux, Sokoloff, and Sutthiphisal 2009), issuance of bonds (Jacoby and Saulnier 1947) or borrowing from banks (Nanda and Nicholas 2014). These sources were generally used to fund more traditional corporate activities (e.g., working capital, tangible investment), but access to these markets could have had implications for innovation decisions by affecting the general financial condition of a company.

The second key distinction between the two organizational forms was their business objectives and strategies. On the one hand, firms operating R&D laboratories were primarily interested in commercializing the technology directly, either by creating new products or by integrating the new technology

⁹ Furthermore, the importance of the local inventors for technology firms is confirmed by an original data collection we conducted. In particular, we digitized investment prospectuses of about 100 early-stage technology firms that were planning to sell securities in Illinois between 1919 and 1924 as discussed in Akkoyun (2018) and Akkoyun and Ersahin (2020), and examine whether the investors in these startups were local. Of the 114 individuals who we identify as early investors and for whom we have information on the city of residence, we find that in 66% of cases these individuals lived in the same city in which the company's headquarters were located, supporting the hypothesis that most of the investors in early-stage innovation were local.

into their preexisting portfolios. On the other hand, independent inventors developed new technologies or products to raise financing to start a business or to monetize inventions through the sale or licensing of patents.

In light of this discussion, a strong parallel can be drawn between independent inventors in the early twentieth century and technological entrepreneurs or startups in modern days. From a financial standpoint, they both heavily rely on external early-stage local investors as a key source of financing. As in the early twentieth century, personal contacts and local investors' networks are still key for raising funds for early-stage innovative ideas (Shane 2008; Gompers et al. 2020).¹⁰ Moreover, the core investment thesis for both independent inventors in the 1920s and modern technological entrepreneurs is fairly similar: both are focused on the development of new technologies or products with the objective of either selling their innovations to an established company or raising financing to commercialize the product in a startup. Last, both organizations are important engines for the development of new ideas and technologies.

While it is undeniable that several aspects of the organization of innovation have changed over the past century, it is also the case that the key economic features through which both firms and technological entrepreneurs operate have remained surprisingly stable. Therefore, independent patents allow us to study the drivers of local technological entrepreneurship over very long time horizons and uncover the dynamics of entrepreneurial development across U.S. counties before data on entrepreneurship became available in the 1980s; and firm patents proxy for innovation produced by more mature organizations.¹¹ We perform two sets of analysis to examine whether our new measure of entrepreneurial activity is correlated with entrepreneurship rates in current data when both are available. Figure A.1 shows that independent innovation rates are correlated with the rates of employment in young (0- to 3-year-old) firms. Moreover, we find a sizable correlation (0.5) between the county-specific rates of patents produced by independent inventors and employment in young firms, providing support for this alternative measure that is available to us during the period we study.

2.2 Innovation during the Great Depression

The Great Depression was one of the largest economic crises in history, with almost a third of all banks suspended and a real GDP decline of 26% (Margo 1993; Richardson 2007). Despite the large literature studying the Great

¹⁰ The key difference is that the financing of early-stage enterprises today is relatively more institutionalized because of the creation of organized angel groups (Kerr, Lerner, and Schoar 2011) and the growth of venture capital (Ante 2008; Kenney 2011).

¹¹ In comparing independent inventors to firms, it is helpful to understand the dynamic connection between the two organizations. While not all independent inventors established a firm, some of them did. Hence, patenting activity by independent inventors always captures innovation happening outside of the boundaries of traditional firms but does not always capture patenting made by early-stage enterprises.

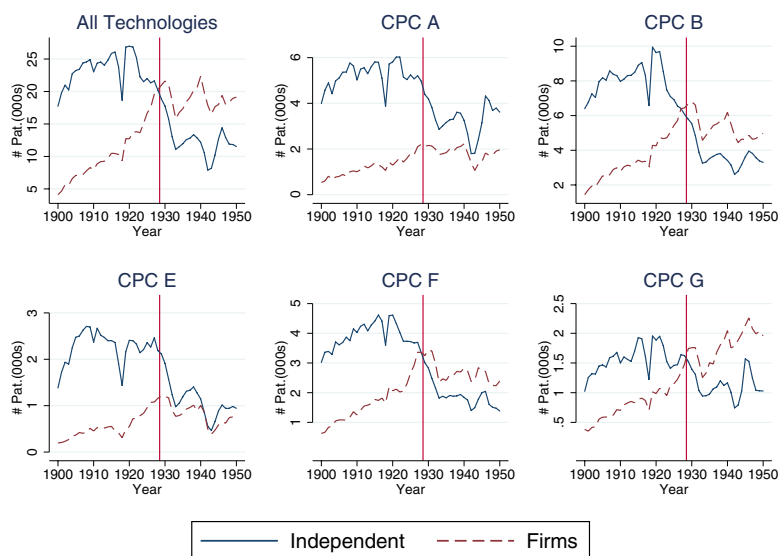


Figure 1

Independent and firm patents: Overall and by technology class

The figure shows the annual number of patents filed by independent inventors and firms for all technologies (top left) as well as the five largest technology classes (based on the 1920s total patenting). In particular, these technology classes are human necessities (CPC A); performing operations or transporting (CPC B); fixed constructions (CPC E); mechanical engineering, lighting, heating, weapons, blasting engines, or pumps (CPC F); and physics (CPC G). The class is reported at the top of each panel. The sample is the universe of all patents granted by the USPTO to U.S. inventors or firms.

Depression, much less is known about how this crisis affected innovative activity. To motivate our study, we start by documenting that the period around the Great Depression was also one of substantial changes in innovation: [Figure A.2](#) shows that there was a decline in annual filing of patents within virtually all major technology classes right around the Great Depression. Furthermore, this decline was driven by a reduction in patenting by independent inventors, and the different pattern between independent and firm patenting holds across the main technologies ([Figure 1](#)).¹²

Clearly, several explanations arise for these trends. One commonly held view is that this shift largely reflects a change in the nature of technologies developed

¹² The number of independent patents declined from 227,000 in the 1920s to 133 in the 1930s, while firm patents increased from 156 to 172,000 over the same time. This secular decline seems unlikely to be explained by institutional changes in the patent system, which was relatively stable over this period. Another explanation is that patent costs may have increased during this period, crowding out independent inventors more than firms. However, this hypothesis is not supported by data on the actual costs of patenting. As shown in [De Rassenfossé and van Pottelsberghe de la Potterie \(2013\)](#), the cost of patenting during this period was fairly low (around \$500 in 2005 dollars). Nominal fees were stable during this period, and they only increased after the 1960s. Real fees increased only a small amount in the early 1930s because of deflation. However, this increase—top of being relatively small—was also short-lived and therefore unlikely to explain the long-term persistence of our findings.

during this period (Teece David 1988; Hughes 2004; Lamoreaux and Sokoloff 2005). In particular, as the discovery and development of new technologies became more capital intensive and complex, firms may have gained a comparative advantage in innovation relative to independent inventors, thanks to firms' ability to finance large investments over long periods and manage projects involving bigger and more specialized teams.

While it seems plausible that technological changes could explain much of the long-run aggregate shift of innovation inside firms, it is less likely to explain the full dynamics of the contraction in independent inventors' patenting in the aftermath of the Great Depression. Since much of the decline in patenting around the Great Depression happened roughly at the same time across all main technologies (Figure A.2), it is unlikely that technological shocks occurred across all technology classes nearly simultaneously (and concurrently with the Great Depression).

In this context, another view is that the Great Depression, which among other things, disrupted access to finance, interacted with these underlying technological changes and accelerated the demise of independent inventors in favor of innovation produced by larger firms. Consistent with this hypothesis, several economic historians have hypothesized that the Great Depression may have severely damaged important aspects of the local entrepreneurial ecosystem, and in particular made it more difficult to raise risk capital. For example, Kenney (2011) writes that "the obstacle to establishing these new firms was a shortage of risk capital, which they believed was due to the changes caused by the Depression that discouraged wealthy individuals from risking their capital in untested firms." In addition, Lamoreaux, Sokoloff, and Sutthiphisal (2009) concludes that "the subsequent dominance of large firms seems to have been propelled by a differential access to capital during the Great Depression." Such reductions in local capital provision and other potential channels that contributed to the decline of technological entrepreneurship in the aftermath of the depression could have been driven by any number of factors (demand or supply) including, but not limited to, wealth shocks among capital providers, cash hoarding from what Friedman and Schwartz (1963) coined a "contagion of fear" (Mitchener and Richardson 2019), declines in small business profits that could have funded entrepreneurial endeavors (Lamoreaux, Sokoloff, and Sutthiphisal 2009), massive labor market disruptions highlighted by national unemployment rates at the peak of the crisis in excess of 20% (Margo 1993), and/or seizure of goods that may have served as inputs for innovative activity that occurred en masse at this time due to repossession following defaults on installment credit (Olney 1999).

Building on this historical evidence, we study how the Great Depression affected subsequent innovation. To start, we show that the local disruptions brought about by the Great Depression were a catalyst for the decline in technological entrepreneurship. To measure this effect, we exploit variation across U.S. counties in the severity of this crisis, which is proxied in our main

specification by bank suspensions. This approach is motivated by the centrality of bank distress in the unfolding of the Great Depression (Bernanke 1983; Gorton, Laarits, and Muir 2019; Mitchener and Richardson 2019) and banks' distress being a good indicator of cross-sectional variation in the severity of the Great Depression in altering the local access to finance. While our approach does not allow us to definitively ascertain that the deteriorating financing environment during the Great Depression was the only channel that explains our results, the historical accounts and some of our evidence suggest that the importance of this channel is highly plausible. For example, we find that proxies for local wealth and capital, rather than more general measures of the decline in economic activity, such as retail sales or unemployment, are more closely linked to immediate drops in independent patenting, suggesting the financial component of the crisis itself likely played an important role in some of our findings. After this initial set of analyses, we also examine whether the decline in independent inventor patents can be interpreted, at least in part, as an acceleration of the process of shifting of innovation from independent inventors to large firms.¹³

3. Data and Descriptive Statistics

3.1 Historical patent data

We use data on the near universe of United States Patent Office (USPTO) patents, representing over 9 million patents from 1836 to 2016, which include filing and grant date, inventors' and assignees' names (if assigned), and their locations. In prior research, patent data have been widely used as a measure of innovation (Hall, Jaffe, and Trajtenberg 2001; Jaffe and Trajtenberg 2002). This data set is collected from the Comprehensive Universe of US Patents (CUSP) (Berkes 2018).¹⁴ Throughout the analysis, we use a patent's filing year because this date is closer to the actual date of invention as compared to the grant year. For all patents, we use patents' technology classification from the USPTO's Cooperative Patent Classification (CPC). For patents filed in 1910–2016, we also have information on citations from patents filed during the same period.¹⁵ Restricting attention to U.S. inventors or assignees in our main sample

¹³ The answers to these questions are important for our understanding of how crises can affect the organization of innovative activity. On the one hand, even if technological forces were already pushing innovation away from independent inventors and toward firms, this does not necessarily imply that we would have observed the same aggregate shift without the Great Depression. As discussed earlier, in this complex context, a large enough external shock may be necessary to allow the transition to happen to its fullest extent and to overcome hysteresis. On the other hand, even if the crisis only accelerated a shift that would have happened eventually, our analysis can shed light on whether a crisis can affect the speed of the transition and its distributional impact across different types of inventors and geographical areas.

¹⁴ For more details on the construction of these data, see Berkes (2018). For more reports on the extra steps taken in terms of cleaning, standardization, and matching to county-level data, we encourage readers to visit the [Internet Appendix A](#) on [Tania Babina's website](#).

¹⁵ As discussed in Berkes (2018), while the quality of the reporting of cited patents improves over time (in particular after 1947), the CUSP still includes information on cited patents in the early part of the sample by extracting

period of 1910–1949 gives us 1.4 million patents. Among these patents, 98% have the inventor's city and state information (which are crucial to aggregate to county-level data), 99% have patent technology classification, and 73% are cited at least once. The resultant data set compares in its comprehensiveness to the data in [Akcigit, Grigsby, and Nicholas \(2017\)](#), who characterize inventors in historical patent data. Relative to [Nanda and Nicholas \(2014\)](#), which looked specifically at the impact of the Great Depression on innovation by firms with R&D laboratories, our data set incorporates patents produced by independent inventors (who produced 55% of patents in our main sample) and patents produced by firms without R&D laboratories.

We separate U.S. patents in two groups: independent patents and U.S. firm patents. The independent inventors' patents are usually unassigned, assigned to the inventor, or assigned to other individuals (e.g., angel investors); patents assigned to firms are usually produced by inventors employed by firms with in-house R&D laboratories who would have been contractually obliged to assign their inventions to their employers ([Lamoreaux and Sokoloff 2001](#); [Lamoreaux, Sokoloff, and Sutthiphisal 2009](#); [Nicholas 2010](#)). Thus, we define independent patents as those granted to inventors residing in the United States that were either unassigned or assigned to individuals at the time of the patent grant date; we define U.S. firm patents as those that were assigned to a U.S. company at the time of the patent grant date. In Section 5.1, we also conduct several robustness tests on the independent inventor definition. [Appendix Figure A.3](#) shows an example of an independent patent, namely, the famous light bulb invention by Thomas Edison, and [Appendix Figure A.4](#) shows an example of a patent assigned to a U.S. firm (General Electric).

Since the key objective of this paper is to examine the impact of regional variation in the severity of the Great Depression on innovation, we use county as a geographic unit of our analysis. We match county-level information to inventors' city-state locations contained in the patents. We are able to match 98% of patents with city-state information. We then create panel data by aggregating patents at each county-period for all U.S. patents, independent U.S. patents, and U.S. firm patents. For all three patent categories, we calculate county-level measures of the number of patents, the number of future citations citing those patents, and the average number of future citations measured as total citations over the number of patents.

patent numbers mentioned in the patent text. Furthermore, it is important to point out that our baseline analysis uses all future citations by patents filed through 2016 (i.e., not only citations from patents published during the Great Depression), a long window that allows us to capture important innovations on which the future generations of patents are built. In our baseline analysis, we do not scale a patent's citation count by the number of citations in its technology class and filing time for a number of reasons. First, the interpretation of the summary statistics of unscaled patents is more intuitive. Second, the results are the same when we do scale, as discussed in Section 5.1. Finally, the inclusion of state-by-time fixed effects in the main analysis essentially scales the citations by the timing of filing, as discussed in [Hall, Jaffe, and Trajtenberg \(2001\)](#).

3.2 County-level measures of severity of the Great Depression

There are potentially different ways to proxy for the severity of the Great Depression in a local market. While all the measures of distress are naturally interrelated, each approach is likely to emphasize a specific aspect of the shock. Our primary proxy for the local severity of the Great Depression is based on bank distress. As we argue below, this measure is likely to largely capture variation in access to finance during this crisis period. To construct this proxy, we follow much of the literature (e.g., [Calomiris and Mason 2003](#)) in using Federal Deposit Insurance Corporation (FDIC) county-level annual reports on active and suspended banks and their deposits from 1920 to 1936. These data are unavailable in the states of Wyoming, Hawaii, and Alaska, and in the District of Columbia, and do not distinguish failures from suspensions. However, [Calomiris and Mason \(2003\)](#) argue that these shortcomings do not interfere with identifying distress empirically. We use 1930 as the starting year for looking at distress because it was not until at least 1930 that financial institutions began to fail in large numbers driven by the Great Depression ([Bernanke 1983](#); [Calomiris and Mason 2003](#)) and following the 1929 stock market crash. Furthermore, given the nature of our measure, we focus on counties with at least one bank in 1929. We indicate that a county had a severe disruption in access to finance during the Great Depression if at least one bank was suspended in that county during 1930–1933, which represents 71% of all counties. This measure provides a relatively simple interpretation of our results and is our primary measure of crisis throughout the paper.¹⁶ We also find consistent results using alternative treatment definitions based on banking data. Building on [Akcigit, Grigsby, and Nicholas \(2017\)](#), we match distress data to the county-level panel data using the location of the first inventor. During this match, we lose 2% of U.S. patents because not all counties have bank distress data. After all these steps, our data contain about 94% of the 1.4 million patents in the main sample. Table 1 presents summary statistics for the county-level data used in the analysis and shows that counties with bank suspensions during the Great Depression are more or less similar with the exception of being somewhat larger than an average county.

While it is plausible to expect that bank distress can affect innovation through several channels, there are also various reasons to expect that variation in this variable largely captures significant differences in financial access for technological entrepreneurs. First, banks were known to be central nodes of information transmission between local inventors that needed financing and wealthy individuals, such as bank clients, local businessmen, landowners, and bank officers and directors themselves, who were willing to back the inventors ([Lamoreaux, Levenstein, and Sokoloff 2006](#)). Hence, failures of

¹⁶ Furthermore, this measure helps assuage concerns of data quality in measurement, as it is unlikely that misreporting would affect the classification. While misreporting could affect the exact number of banks experiencing distress, it is unlikely that errors will completely miss all reports from distressed areas.

Table 1
County-level summary statistics for all and for distressed counties

| | <i>All Counties</i> | | | <i>Counties w/ Suspensions</i> | | |
|--|---------------------|----------|--------|--------------------------------|----------|--------|
| | Mean | Std.Dev. | NumObs | Mean | Std.Dev. | NumObs |
| <i>1920s Patenting per county (log):</i> | | | | | | |
| Number Patents | 2.72 | 1.63 | 2975 | 3.04 | 1.62 | 2129 |
| Number Citations | 3.24 | 1.96 | 2975 | 3.60 | 1.92 | 2129 |
| Average Citations/Patent | 1.00 | 0.47 | 2975 | 1.04 | 0.41 | 2129 |
| <i>Independent:</i> | | | | | | |
| Number Patents | 2.60 | 1.50 | 2975 | 2.90 | 1.48 | 2129 |
| Number Citations | 3.10 | 1.84 | 2975 | 3.45 | 1.79 | 2129 |
| Average Citations/Patent | 0.99 | 0.48 | 2975 | 1.03 | 0.42 | 2129 |
| <i>US Firms:</i> | | | | | | |
| Number Patents | 1.05 | 1.65 | 2975 | 1.25 | 1.78 | 2129 |
| Number Citations | 1.29 | 2.01 | 2975 | 1.52 | 2.15 | 2129 |
| Average Citations/Patent | 0.49 | 0.66 | 2975 | 0.56 | 0.67 | 2129 |
| <i>Crisis County-level Variables:</i> | | | | | | |
| Bank Distress | 0.72 | 0.45 | 2975 | 1.00 | 0.00 | 2129 |
| Bank Distress % | 0.30 | 0.28 | 2975 | 0.42 | 0.24 | 2129 |
| Agric Land Value %Chg '25-35 | -0.33 | 0.18 | 2959 | -0.36 | 0.17 | 2119 |
| <i>Misc. County-level Variables:</i> | | | | | | |
| Population, 1920 (log) | 9.81 | 0.98 | 2948 | 9.99 | 0.94 | 2116 |
| Unemployment per Capita, 1937 | 0.04 | 0.02 | 2971 | 0.04 | 0.02 | 2126 |
| Chg Retail Sales, 1929-1933 | -0.48 | 0.23 | 2941 | -0.49 | 0.21 | 2105 |
| Number Banks, 1929 | 8.12 | 10.28 | 2975 | 9.88 | 11.54 | 2129 |
| Man. Workers % Pop. 1929 | 5.55 | 7.33 | 2942 | 5.87 | 7.37 | 2105 |

The table shows summary statistics across all counties and only counties distressed during the Great Depression, according to the main definition used in the paper. Note that since we do not have the number of working-age people seeking employment, the unemployment per capita is proxied as the number of unemployed people divided by the 1930 population count. For patent count variables, we also apply a log-transformation, consistent with the analyses in the main tables. *Bank distress %* is calculated as the cumulative number of bank suspensions in 1930–1933 as a share of total banks in 1929. Independent denotes patents by inventors residing in the United States that were either unassigned or assigned to individuals at the time of the patent grant date. Firm are patents that were assigned to a U.S. company at the time of the patent grant date.

local banks can sever information flows and destroy relationship capital, which are important pieces of the local innovation ecosystem. Second, local bank distress could be linked to the reduced ability or willingness of local wealthy individuals to invest in risky technological projects. Indeed, new technology companies were in large part funded by local investors (Section 2), and these investors were highly exposed to the economic success of the local economy.¹⁷ Lastly, one could imagine that bank suspensions could also affect local entrepreneurs directly, by a reduction in bank lending to them. However, bank lending was not a major direct source of financing for independent inventors at this time, and therefore it is also important to highlight that this factor is unlikely to play a significant role during this time.

In our empirical analysis, we also employ alternative approaches to identify variation in the intensity of the Great Depression in the local market. In

¹⁷ The idea that investors were also likely to be sensitive to local shocks appears consistent with data. Using data from the Study of Consumer Purchases (1935–1936), we find that only 10% of business owners, that is, the typical investor in early-stage companies, obtain any income from stocks and bonds, while exposure to real estate is much larger. Overall, 42% of business owners report owning at least 50 acres of land during this time. This is consistent with sensitivity to local shocks among important capital contributors in these innovation ecosystems.

Section 5.1, we compare the results obtained using different proxies as a way to generate insights about which aspect of the crisis is more likely to be behind our effects. As a first alternative, we measure the reduction in the value of real estate during the Great Depression. The agricultural census provides survey data on the average price of farmland per acre at the county level both before (1925) and following (1935) the onset of the Great Depression that has been validated using hand-collected data by [Rajan and Ramcharan \(2015\)](#). We use these to compute the percentage change in county-level agricultural land values from 1925 to 1935. As can be seen in Table 1, prices declined substantially over this period, and there is substantial variation in the size of this decline across counties, which we take advantage of in our robustness checks. Similar to bank distress, this measure is likely to proxy for local shocks to capital, which in turn may also affect the ability of local innovators to access financing.¹⁸ We also consider other metrics that are more likely to proxy for more general economic decline rather than financial distress in a county. Following the literature, we examine variation across counties in unemployment per capita in 1937 and the change in retail sales in 1929–1933.¹⁹ We discuss the interpretation of these measures more extensively in Section 5.1.

3.3 Inventor panel data

Although county-level patent data are well suited to measure how local distress affects aggregate local innovation, this level of analysis cannot speak to the micro-mechanisms driving aggregate changes in patenting or to which types of inventors were more affected by the Great Depression. For example, aggregate changes can be driven through migration of inventors across different organizational forms of innovation (e.g., from patenting independently to working for firms). Moreover, patent text does not tell us anything about inventors, which makes it impossible to examine which inventors might have been affected more by the crisis. To examine such mechanisms, we build longitudinal data on inventors and their place of inventing in two steps.²⁰

¹⁸ As we discussed earlier in this section, investors in local technology companies were in large part local wealthy individuals, which at the time were heavily exposed to local shocks, in particular in the real estate sector.

¹⁹ We use unemployment in 1937, the lowest point of the second recession during the 1930s, and follow [Boustan, Fishback, and Kantor \(2010\)](#) in proxying for labor market disruptions during the 1930s by computing the unemployment per capita based on population estimates from the 1930 census. This is substantially lower than the unemployment rate since the denominator includes everyone, not just the estimated total number of noninstitutionalized civilian working age population - which are harder to reliably estimate at this time.

²⁰ We build these data because the USPTO does not assign inventors a unique identifier, and linking inventors by name across patents is not sufficient to match individual inventors across time: some common names are recurrent across decades and counties and potentially refer to different people with the same name. Moreover, the commonly used modern methods of inventor disambiguation (e.g., [Li et al. 2014](#)) using additional variables, such as an inventor's address and coinventors, assignee name, and patent technology class, are not practical for our setting. First, one of our key interests is measuring the potential migration of independent inventors into firms and across geographic space. Hence, we cannot use the address or assignee name to link inventors across patents. Second, since 90% of patents filed in the first half of the century are single-inventor patents, coinventor networks also provide limited variation for matching. Finally, important technological advancements in the 1920s and the 1930s might create biased matches if we use technology classification in the linking process.

In the first step, we match inventors in patents filed from 1905 to 1949 to the complete count U.S. census (1910, 1920, 1930, or 1940) that is the closest to their patent filing year (e.g., 1905–1914 to the 1910 census). Similar to [Akcigit, Grigsby, and Nicholas \(2017\)](#), we use inventor names and county of residence on the patent text to match to individuals in census, filter duplicate matches based on middle initials and age (individuals from 17 to 66 years old in the census), and discard non unique matches.²¹ At the strictest round of matching, which resembles what is done in [Akcigit, Grigsby, and Nicholas \(2017\)](#), we uniquely match 45% of inventors. This number is similar to the 39% match rate in [Akcigit, Grigsby, and Nicholas \(2017\)](#). The additional rounds of matches as well as the new filtering method bring the percentage of unique matches to about 65%. Consistent with prior work ([Akcigit, Grigsby, and Nicholas 2017](#); [Sarada, Andrews, and Ziebarth 2019](#)), we find that inventors tend to be older, male, and married. We also find that the inventors tend to be much more highly educated and earn much more than an average person, which is similar to [Akcigit, Grigsby, and Nicholas \(2017\)](#). [Appendix Figures A.5](#) and [A.6](#) also show that, compared to other males, inventors earn more and own more-valuable houses. Intuitively, we find that inventors have a different distribution of occupations than the general population. For example, inventors are three to four times *more* likely to be managers, and three to four times *less* likely to be farmers.²²

In the second step, we longitudinally link uniquely matched inventor-census individuals to three other censuses (e.g., inventors matched to the 1910 census are then matched to 1920, 1930, and 1940 censuses using time-invariant individual-level information in 1910 and other censuses). We follow leading work on linking individuals across censuses (e.g., [Long and Ferrie 2013](#); [Abramitzky, Mill, and Perez 2019](#); [Abramitzky et al. 2021](#)) by matching individuals based on their year and place of birth, which are both well populated in all censuses of interest. We match between 25% and 55% of records, depending on how far apart censuses are, which are similar rates to those in prior research efforts. These two steps produce a longitudinal sample of

²¹ To increase the potential rate of matching, we introduce two additional steps. First, we perform 12 different rounds of matching from most to least precise, with exact matching in the first round to partial name matching in later rounds. Second, we create an inventor-like job filter to identify likely inventors in duplicate matches. For example, there could be two possible census records for Thomas Edison: one as a laborer and the other as an inventor. The inventor census record is most likely to be the correct Edison. We performed an extensive examination of the matched data to determine that matches in rounds 1 through 9 provide high-quality matches on the order of accuracy of 85%–95%, while rounds 10–12 did not offer improvements. Hence, we only consider matches in rounds 1–9 in all further analyses. The detailed process of matching and the full set of matching statistics can be found in Internet Appendix B, which is available on [Tania Babina's website](#).

²² For brevity, we only report the distribution of occupations for inventors versus noninventors for the 1930 census matched sample in [Appendix Figure A.7](#), but all statistics for each decade are available in online appendix B on [Tania Babina's website](#).

Table 2
Summary statistics for independent inventor and firm patents

| | Number of Observations | Mean | Std Dev | 50th Pctl | 75th Pctl | 90th Pctl | 95th Pctl | 99th Pctl |
|--|---------------------------|------|------------|--------------|--------------|--------------|--------------|--------------|
| Panel A: Patent-level Data | | | | | | | | |
| <i>Patents filed in 1910–1929</i> | | | | | | | | |
| Independent Number Citations | 473,517 | 2.1 | 4.1 | 1 | 3 | 6 | 8 | 16 |
| Firm Number Citations | 251,773 | 2.1 | 3.8 | 1 | 3 | 6 | 8 | 16 |
| <i>Patents filed in 1930–1949</i> | | | | | | | | |
| Independent Number Citations | 250,930 | 5.4 | 7.6 | 3 | 7 | 12 | 17 | 31 |
| Firm Number Citations | 348,039 | 5.7 | 7.7 | 4 | 7 | 13 | 18 | 33 |
| Panel B: County-decade-level Data | | | | | | | | |
| <i>Patents filed in 1910–1929</i> | | | | | | | | |
| Independent Number Patents | 5,950 | 78.8 | 546 | 13 | 34 | 99.5 | 217 | 1245 |
| Firm Number Patents | 5,950 | 42.2 | 381 | 0 | 3 | 25.5 | 92 | 885 |
| Independent Number Citations | 5,950 | 166 | 1,286 | 21 | 59 | 196 | 441 | 2,689 |
| Firm Number Citations | 5,950 | 90.2 | 831 | 0 | 5 | 50.5 | 193 | 2,063 |
| Independent Average Citations | 5,950 | 1.7 | 1.4 | 1.5 | 2.2 | 3 | 3.6 | 6.1 |
| Firm Average Citations | 5,950 | 0.9 | 2.3 | 0 | 1.4 | 2.7 | 3.7 | 7 |
| <i>Patents filed in 1930–1949</i> | | | | | | | | |
| Independent Number Patents | 5,950 | 41.3 | 304 | 4 | 13 | 46 | 107 | 715 |
| Firm Number Patents | 5,950 | 57.6 | 420 | 1 | 5 | 39 | 147 | 1,435 |
| Independent Number Citations | 5,950 | 224 | 1,752 | 17 | 62 | 241 | 556 | 3,928 |
| Firm Number Citations | 5,950 | 329 | 2,389 | 0 | 26 | 219 | 784 | 8,269 |
| Independent Average Citations | 5,950 | 3.9 | 3.6 | 3.8 | 5.5 | 7.3 | 9 | 14.4 |
| Firm Average Citations | 5,950 | 2.9 | 4.4 | 0 | 5 | 7.6 | 10 | 20 |

The table shows summary statistics across independent inventor patents and patents assigned to firms. Independent denotes patents by inventors residing in the United States that were either unassigned or assigned to individuals at the time of the patent grant date. Firm are patents that were assigned to a U.S. company at the time of the patent grant date. Panel A shows statistics for patent-level data, and panel B shows data on the county-decade level. Each panel shows statistics for patents filed during 20 years before and 20 years since the start of the Great Depression. For county-level data, *Number patents* refers to the total number of patents within each county-decade; *Number citations* is the sum of citations given to patents filed within each county-decade; and *Independent average citations* is calculated as the number of county-decade citations divided by the number of county-decade patents (it is set to zero when there are no patents).

patenting individuals across four decades, allowing us to track inventors across geographic space and to obtain inventor characteristics.²³

3.4 Descriptive analysis

The comprehensive nature of our patent data allows us to provide some key descriptive evidence on the population of patents by the two key innovation-producing groups in the first half of the twentieth century: independent and firm patents. Consistent with prior work, panel A of Table 2 shows much lower patenting share by independent inventors in the 1930–1949 period (42%)

²³ While we follow the state-of-the-art methods to match inventors to censuses, one concern might be that the matching rates can generate spurious results if the matching rates correlate with the key independent variable, that is, county-level bank distress. However, the data are not consistent with this concern. In Section 10 of Internet Appendix B (available on [Tania Babina's website](#)), we regress the matching rates: (1) to each census, and (2) across censuses on our main treatment variable ($Crisis = 1$) and find very small and insignificant differences in the matching rates in counties with and without bank suspensions during the Great Depression years 1930–1933. Moreover, we also are able to reproduce our main results (i.e., Table 3) based in a subsample of inventors that are matched to the censuses. These three tests provide concrete evidence that the biases in match rates of inventors to and across the complete count censuses are likely not a concern for the interpretation of our results

as compared with the earlier 1910–1929 period (65%). When it comes to the importance of patents, panel A of Table 2 shows that, compared to firm patents, independent patents received a similar average number of citations both before and after the Great Depression. This is interesting because both Lamoreaux and Sokoloff (1999) and Nicholas (2010) find that independent patents were more highly cited than firm patents in samples that include earlier subperiods not included in our analysis.

Using inventor characteristics obtained from the census data, we also document that independent inventors are much more likely to be entrepreneurs compared to firm inventors, which is intuitive and suggests that independent inventors were not only “garage inventors” but also pursued commercialization of their ideas. Internet Appendix B shows this to be the case in every decade from 1910 to 1940.²⁴ In Appendix Figures A.8 and A.9, we also document that independent inventors (as compared to inventors producing patents within firms) are (1) more likely to be female; (2) are, on average, 2 years older; (3) 4% more likely to be immigrants (this is a quarter more compared to 16% of immigrants among firm inventors); and (4) 5% less likely to be married (compared to 80% of firm inventors being married). The differences in immigration rates are particularly interesting because immigrants tend to be more entrepreneurial in more recent periods (for a review, see Kerr and Kerr 2020), and our evidence suggests that this was true even 100 years ago.

Aggregating firm and independent patents at the county-decade level, shows that the number of firm and independent patents are highly correlated (correlation of 82%). Panel B of Table 2 contains statistics on the distribution of firm and independent patents at the county-decade level and shows a wide distribution of patents across U.S. counties, consistent with the idea that innovation was far less concentrated than at present. Similarly, Appendix Figure A.10 shows the ubiquity of independent inventions across U.S. counties during the 1920s, which supports the idea that pockets of technological entrepreneurship were widespread across the United States prior to the 1930s.

In fact, Lamoreaux and Levenstein (2014) point to Cleveland, Ohio, as a famous example of one of these pockets of innovation in the 1920s that experience declines during the Great Depression coming from a fall in new inventors. Consistent with this prior work, we note that in our data that Cuyahoga County, home to Cleveland, had the seventh most independent patents of any county in the country in the 1920s that experienced a bank suspension during the Great Depression. From 1930 to 1933, the county experienced a substantial disruption in its banking sector and independent patents fell by 30% in the 1930s relative to the 1920s, while at the same time firm patents actually rose by 14%. While historical accounts of the role that disruptions to local capital during the Great Depression may

²⁴ All statistics are available in online appendix B on Tania Babina’s website (<https://www.taniababina.com/>).

have played in Cleveland's innovation declines are fascinating case studies (Lamoreaux, Levenstein, and Sokoloff 2007; Lamoreaux and Levenstein 2014), our data suggests that these experiences are also likely to be broadly representative of many of the major innovation hubs that experienced distress. The average reduction in independent patents among the seven largest counties (based on independent patenting in the 1920s that had bank suspensions in the 1930s) was 35%, with Cleveland actually less of a reduction than average, while firm patenting fell by less than 1%. By contrast, the seven largest innovation hubs in 1920 that experienced no bank distress during 1930–1933 saw an average reduction in independent patenting of less than 10%. While any discussion of longer-term fallout in particular cities will obviously be speculative and coincident with other factors, it is also interesting to note the persistence of the decline in innovation by some of the largest innovation hubs of this time (based on 1920s independent patent production) that experienced substantial distress during the Great Depression. This includes not just Cuyahoga, but also Wayne (fifth in the 1920s and home to Detroit) and Allegheny counties (eighth in the 1920s and home to Pittsburgh). By contrast, San Mateo County in California was also one of the largest innovation hubs of the 1920s, but perhaps because of a large Bank of America presence, potentially driven by the local residency of its founder (James and James 1954), it was far less exposed to capital disruptions during the Great Depression (Quincy 2019), and actually saw an increase in independent patenting of 21% during the 1930s, and continues to be a major innovation hub to this day.

Within the major innovation hubs that experienced distress, the largest innovator of the 1920s, Cook County, home of Chicago, also provides an illustrative case study. As shown by Mitchener and Richardson (2019), Chicago experienced a significant shock to its banking sector, in part because of the pyramiding structure of bank reserves which was leftover from the national banking period. In fact, Chicago had the highest bank failure rate of any urban area in the United States. (Guglielmo 1998; Calomiris and Mason 1997; Postel-Vinay 2016). The result was a severe financial crisis in Chicago. What started with banks going under quickly spilled over more broadly into overall economic turmoil (Bernanke 1983). In our data, we find that innovation also changed dramatically in Cook County during this period of economic distress. Despite an increase in patents filed by independent inventors in Cook County in each of the two decades preceding the Great Depression, independent patents filed would plummet by 47% in the 1930s, while those by firms would fall only 9%. Independent patenting would continue to fall in each of the following three decades, while firm patenting largely recovered to precrisis levels.²⁵ Despite the large decline (29%) in total patenting in the 1930s relative to 1920, total

²⁵ This appears to occur for both the entry and exit of inventors and among inventors patenting in both decades. Among all U.S. counties in our sample, Cook County actually has the most serial inventors who patent independently before the Great Depression, but in firms after.

future citations over the next 70 years from patents filed during this period would actually rise 34%.

While these examples are obviously insufficient evidence on their own, they are certainly consistent with the better identified evidence we provide next in the paper.

4. Empirical Design

The key objective of this paper is to examine the impact of regional variation in the severity of the Great Depression on patent filing. Specifically, we use a difference-in-differences specification that compares innovation across counties that experienced different level of crisis severity. In our primary specification we exploit variation across counties in bank distress. To remove the effect of regional business cycles and changes in state-level regulation, we ensure all our specifications include state-by-time fixed effects.²⁶ We also include county fixed effects to control for time-invariant differences across counties. Our primary specification is

$$\ln(\text{Innovation})_{cst} = \alpha_c + \gamma_{st} + \beta \text{Crisis}_{cs} \times \text{After1929}_t + X'_{cst} \zeta + \epsilon_{cst}, \quad (1)$$

where c denotes a county, s denotes a state, and t denotes time (defined in decades if not specified otherwise).²⁷ $\ln(\text{Innovation})_{cst}$ is the natural logarithm of the number of patents, the total future patent citations, or the average citations per patent;²⁸ α_c are county fixed effects; γ_{st} are state-by-time fixed effects; Crisis_{cs} is our main treatment variable: in our primary specification this denotes the degree of bank distress and equals one if the county had at least one bank suspended in 1930–1933, and zero otherwise, but we will also consider alternative approaches to measuring the severity of the Great Depression across counties; After1929_t equals 1 for observations starting in 1930, and zero otherwise. X_{cst} includes county-specific controls discussed later; these controls are usually measured before the Great Depression and interacted with the post dummy, After1929_t . The estimate of the effect of the crisis on local innovation is given by β . We cluster standard errors by county, which is the level of our treatment (Bertrand, Duflo, and Mullainathan 2004).

²⁶ This approach allows us to net out any aggregate changes in the legal or innovation environment around this period. For instance, Beauchamp (2015) documents a rise in patent litigation in the late 1930s, which may affect the incentive to innovate (e.g., Mezzanotti 2020; Mezzanotti and Simcoe 2019).

²⁷ The higher level of aggregation, as compared to the annual level, allows us to reduce noise due to some counties not having patents filed each year and avoid the well-known problem of potential biases in regression estimates when a dependent variable has many zeros. However, as we discuss later, we find consistent results with alternative aggregation methods (i.e., using 1 or 5 years).

²⁸ As is standard practice, we add one to the number of patents before taking the logarithm in order to avoid dropping counties without any patents over a given period. As we discuss later, this data transformation turns out to be unimportant for our results because about 90% of counties have at least one patent filed each decade.

5. Results

5.1 Decline in independent innovation in the aftermath of the Great Depression

In this section, we explore how the Great Depression altered patenting activity by the largest organizational form of innovation at the time-independent inventors. We also address potential threats to our empirical strategy.

5.1.1 Main findings. In Table 3, we start by showing that counties more exposed to the crisis, proxied by bank suspensions during the Great Depression, saw a reduction in the quantity of overall patenting (column 3), driven by a decline in independent patents (column 1), and no change in firm patenting (column 2). We focus on the significant result for independent innovation and revisit firm innovation in the next section. Our estimates suggest that counties that were more exposed to the crisis saw a drop in independent patenting around the Great Depression that was 13% higher than counties with less duress.

Before we can causally interpret the results that the local economic severity of the Great Depression led to the decline of independent innovation, it is important to provide more evidence that can help us rule out some of the confounding factors that could affect this result. The key identifying assumption in a difference-in-differences setting is that, in the absence of the Great Depression, counties that were more exposed to the shock would

Table 3
Local severity of the crisis during the Great Depression and innovation quantity

| | (1) Ln(# Ind. Patents+1) | (2) Ln(# Firm Patents+1) | (3) Ln(# Total Patents+1) |
|--------------------|-----------------------------|-----------------------------|------------------------------|
| Crisis X After1929 | -0.127*** (0.029) | 0.016 (0.027) | -0.105*** (0.031) |
| StateXTime FE | Y | Y | Y |
| County FE | Y | Y | Y |
| Start Decade | 1910 | 1910 | 1910 |
| End Decade | 1940 | 1940 | 1940 |
| Adj R-Sq | 0.895 | 0.896 | 0.903 |
| Obs | 11,900 | 11,900 | 11,900 |

The table shows estimates from a difference-in-differences regression of the number of patents by patent type on a proxy for the local severity of economic crisis during the Great Depression. The estimation strategy relies on cross-sectional variation in distress across U.S. counties within a state. The sample is the near universe of all patents granted by the U.S. Patent and Trademark Office (USPTO) to either U.S. inventors or U.S. firms. The unit of observation is county-decade, for the period 1910–1940. In column 1, we limit the sample to independent patents and define the dependent variable as the logarithm of one plus the number of independent patents filed over 10-year periods within each county. Independent denotes patents by inventors residing in the United States that were either unassigned or assigned to individuals at the time of the patent grant date. In column 2, we limit the sample to patents assigned to U.S. firms and define the dependent variable as the logarithm of one plus the number of U.S. firm patents filed over 10-year periods within each county. Firm patents are those that were assigned to a U.S. company at the time of the patent grant date. In column 3, the dependent variable is the logarithm of one plus the number of all U.S. patents filed over 10-year periods within each county. *Crisis* is an indicator variable equal to one for counties with at least one bank suspension during the Great Depression years of 1930 through 1933, inclusive. The estimates of the effect of local distress on patents are the coefficients for the interaction between *Crisis* and the *After1929* indicator, which equals one for the observations starting from the 1930s decade. All columns include state-by-time and county fixed effects. Standard errors are clustered at the county level and reported in parentheses. * $p < .1$; ** $p < .05$; *** $p < .01$.

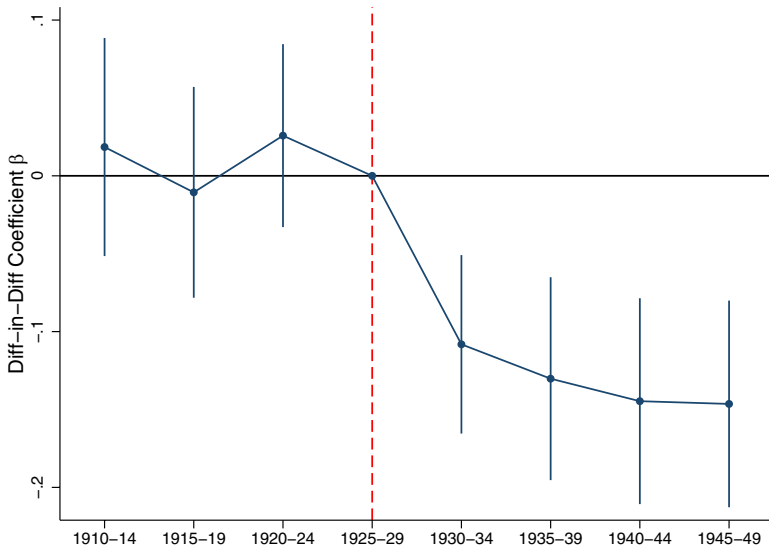


Figure 2

Local severity of the crisis during the Great Depression and independent innovation quantity

The figure shows estimates from a difference-in-differences regression of the number of independent patents on a proxy for the local severity of economic crisis during the Great Depression. The estimation strategy relies on cross-sectional variation in distress across U.S. counties within a state. The sample is the near universe of all independent patents granted by the U.S. Patent and Trademark Office (USPTO). Independents are patents by inventors residing in the United States that were either unassigned or assigned to individuals at the time of the patent grant date. The unit of observation is county-time, where time is 5 years. The dependent variable is the logarithm of one plus the number of independent patents filed over 5-year periods within each county. *Crisis* is an indicator variable equal to one for counties with at least one bank suspension during the Great Depression years of 1930 through 1933, inclusive. The estimates of the effect of local distress on independent innovations are the coefficients for the interaction between *Crisis* and 5-year indicators that measure the relative change in patenting in areas with high distress relative to the reference period of 1925–1929. We plot betas and 95% confidence intervals from a difference-in-differences regression:

$$\ln(\text{Number Patents} + 1)_{cst} = \alpha_c + \gamma_{st} + \sum_t \beta_t 1_t \text{Crisis}_{cs} + \epsilon_{cst}, \quad (2)$$

where c denotes county, s – state, and t – 5-year period. α_c is county fixed effects; γ_{st} is state-by-time fixed effects; and 5-year indicators equal to one for a given time period, and zero otherwise. Standard errors are clustered at the county level.

have had a similar trend in innovation relative to counties less affected by it. Although this assumption is fundamentally untestable, we can examine whether more-affected counties already had differential trends in innovation before the crisis: if our results are explained by an omitted variable that is unrelated to the crisis, we might expect to find differential innovation patterns before the Great Depression.

To start, we examine the dynamics of the effects using a longer panel (1900–1950) organized over 5-year windows. Figure 2 provides evidence that is inconsistent with this concern: before the 1930s, counties that experienced distress during the Great Depression did not differ in their relative trends in independent inventors’ activity. This changed sharply during the 1930–1934

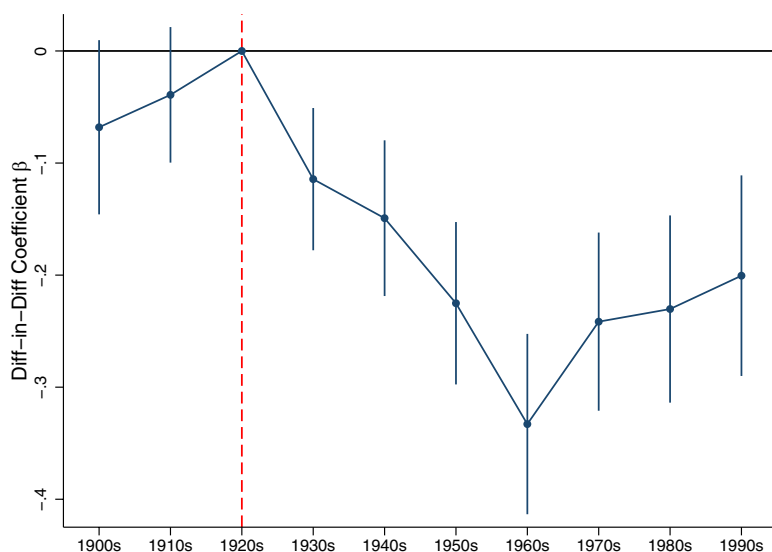


Figure 3

Local severity of the crisis during the Great Depression and long-run independent patenting

The figure shows estimates from a difference-in-differences regression of the number of independent patents on a proxy for the local severity of economic crisis during the Great Depression looking over more than a century from 1900 to 1999. The estimation strategy relies on cross-sectional variation in distress across U.S. counties within a state. The sample is the near universe of all independent patents granted by the U.S. Patent and Trademark Office (USPTO). Independent refers to patents by inventors residing in the United States that were either unassigned or assigned to individuals at the time of the patent grant date. The unit of observation is county-time, where time is a decade. The dependent variable is the logarithm of one plus the number of independent patents filed over 10-year periods within each county. *Crisis* is an indicator variable equal to one for counties with at least one bank suspension during the Great Depression years of 1930 through 1933, inclusive. The estimates of the effect of local distress on independent innovations are the coefficients for the interaction between *Crisis* and 10-year indicators. In particular, they measure the relative change in patenting in areas with high distress relative to the reference period of 1920–1929. We plot betas and 95% confidence intervals from a difference-in-differences regression:

$$\ln(\text{Number Patents} + 1)_{cst} = \alpha_c + \gamma_{st} + \sum \beta_t 1_t \text{Crisis}_{cs} + \epsilon_{cst} \quad (3)$$

where c denotes county, s – state, and t – decade; α_c is county fixed effects; γ_{st} is state-by-time fixed effects; and 10-year indicators equal to one for a given time period, and zero otherwise. Standard errors are clustered at the county level.

period when we document a sudden and persistent reduction in innovation by technological entrepreneurs in more severely affected areas.²⁹ In fact, in Figure 3, we show that the decline in independent patenting persisted in every decade for the next 70 years. Therefore, not only did the Great Depression lead to a large reduction in technological entrepreneurship in the aftermath of the crisis but also its effects played an important role in shaping regional variation in U.S. innovation for many decades following the crisis. While we certainly are not the first to find any longer-lasting effects from the Great Depression (e.g., Lee and Mezzanotti 2017), most disruptions are short-lived

²⁹ The annual version of the same analysis, shown in Appendix Figure A.11, confirms this sudden decline.

(e.g., Ziebarth 2013), making our findings of the persistence of the decline in innovative activity by these technological entrepreneurs important to document and interesting to understand. We examine this in Section 5.3.

This observed decline in independent innovation is robust to our choices in variable measurement. First, in Table A.1 we show that our findings are robust to using alternative measures of innovation outcomes. In column 1, we show that our results are mainly driven by those independent inventors that self-identified in the census as “entrepreneurs” (working for themselves as opposed to salaried employees). This result confirms that the decline documented earlier captures a real reduction in entrepreneurial activity. It also provides additional validation for using independent patents as a measure of technological entrepreneurship. Furthermore, columns 2–6 show that our findings are unchanged if we conduct alternative transformations of the innovation outcomes.³⁰ Finally, we show that the results hold using alternative treatment definitions: in particular, we find similar results using different transformations of bank suspensions as a measure of local economic distress (columns 1–3 of Table A.2).³¹

5.1.2 Different measures of local distress. So far, we have used bank distress to measure variation in the acuteness of the crisis across counties. We now examine how our results differ when we use alternative ways to identify areas that are harder-hit by the Great Depression. This analysis is useful because it can help us better understand which aspect of the crisis was particularly important in explaining our effects. While all these measures are naturally interrelated, different proxies should capture different aspects of the crisis (see Section 3.2 for a more detailed discussion). In Table 4, we present these results. In general, we find qualitatively similar results when we exploit variation in changes in agricultural real estate values during the

³⁰ One concern in our setting is related to the presence of zeros in patent data, which led us to add a unit to the traditional log-transformation. In column 2, we construct the outcome without adding the unit, therefore dropping the zero observations and focusing on a purely intensive margin. We find that our estimates are very similar to the main one as reported in Table 3. We also show robust results to using two alternative transformations to our log-transformation approach, such as employing the commonly used inverse hyperbolic sine transformation or adding a smaller base (0.5) to our outcome (columns 3 and 4). In unreported results we also obtain similar findings where zeros no longer matter, such as examining just the level of patenting, the patents per capita, or the symmetric growth rate (Decker et al. 2014) between 1920 and 1930. Furthermore, in column 5, we use the same transformation as in the rest of the paper but show that the results are robust to also including as part of independent patents those patents that are assigned to a firm whose name contains the inventors’ last or first name (e.g., eponymous firm names as in the “Thomas Edison Electric Co.” which are likely founded by the inventors or their family members). This test helps rule out that the effects might be driven by some relabeling from independent to firm patents by inventor-entrepreneurs in more-distressed areas. Finally, we also find consistent results if we focus on patents with positive citations (column 6).

³¹ For instance, the effects are consistent when splitting the sample at the median of distress (column 2), measured as the share of 1929 deposits suspended in 1930–1933, or defined as distressed counties that are not in the bottom tercile in terms of distress (column 3). Note that since the choice of cutoff for being “treated” alters both the set of treatment and control counties, it is not obvious ex ante which measure is likely to yield larger responses.

Table 4
Different measures of local severity during the Great Depression and innovation quantity

| | Ln(# Independent Patents+1) | | | | | |
|----------------------------------|-----------------------------|------------------|------------------|----------------------|----------------------|----------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| High Land Price Drop X After1929 | -0.131*** (0.025) | | | -0.120*** (0.025) | | |
| High Unempl. X After1929 | | 0.021 (0.025) | | | 0.022 (0.024) | |
| High Sale Drop X After1929 | | | 0.018 (0.024) | | | 0.024 (0.024) |
| High Bank Distress X After1929 | | | | -0.118*** (0.028) | -0.128*** (0.029) | -0.125*** (0.029) |
| StateXTime FE | Y | Y | Y | Y | Y | Y |
| County FE | Y | Y | Y | Y | Y | Y |
| Start Decade | 1910 | 1910 | 1910 | 1910 | 1910 | 1910 |
| End Decade | 1940 | 1940 | 1940 | 1940 | 1940 | 1940 |
| Adj R-Sq | 0.894 | 0.894 | 0.892 | 0.894 | 0.894 | 0.892 |
| Obs | 11,836 | 11,884 | 11,764 | 11,836 | 11,884 | 11,764 |

The table shows that how different measures of local distress during the Great Depression helps explaining the response. The sample is the near universe of independent patents granted by the U.S. Patent and Trademark Office (USPTO). Independent denotes patents by inventors residing in the United States that were either unassigned or assigned to individuals at the time of the patent grant date. The unit of observation is county-decade, for the period 1910–1940. In all columns, the dependent variable is the logarithm of the number of independent patents filed over 10-year periods within each county. The independent variable changes across columns. In column 1, we define an area as high distress if the county experienced a decline in real estate prices (1935–1925) above the median. In column 2, we define an area as high distress if the county had an unemployment per capita in 1937 (unemployed people in 1937/county-level populations from the 1930 census) above the median. In column 3, we instead use data on 1929–1933 sales growth, also splitting at the median. In columns from 4 to 6, we use the same variables, but now also include our main definition of local distress based on bank distress. The estimates of the effect of distress on patents are the coefficients for the interaction between Crisis (defined differently column by column) and the After1929 indicator, which equals one for the observations starting from the 1930s decade. All columns include state-by-time and county fixed effects. Standard errors are clustered at the county level and reported in parentheses.

* $p < .1$; ** $p < .05$; *** $p < .01$.

Great Depression (column 1).³² However, the same does not hold when we use variables that are more likely to capture economic rather than financial distress. In particular, neither unemployment (column 2) nor retail sales growth (column 3) predict significant changes in independent innovation.³³ Our conclusions also do not change if we include bank distress in the analysis as an additional control variable (columns 4–6).³⁴

³² We use the 1925–1935 change because data for 1933 are not available. In Table A.2, we also show that (like for bank distress), our results using real estate values do not crucially depend on the way we construct this variable. In fact, we find similar effects when we define as highly affected a location that experienced a decline in real estate values in the top quartile (column 4) or above the median (column 5).

³³ The lack of significance for unemployment does not necessarily imply that economic distress stemming from labor market disruptions was not relevant in explaining our findings. At least in part, this result may reflect the imperfect nature of this empirical proxy for the disruptions during the worst part of the Depression in 1933.

³⁴ When interpreting these findings it is also important to keep in mind that these unemployment and sales growth control variables may capture variation in the intensity of the crisis, and more specifically it is possible that their magnitude is affected by local bank distress, causing a “bad control” problem. However, their inclusion may be informative to gauge the extent to which our results may be affected by some omitted variable that happens to be correlated with the unfolding of the crisis, and therefore with changes in unemployment or sales.

Separating the different channels through which the Great Depression may affect independent innovation is complicated, because economic and financial distress at the local level are interconnected phenomena. However, this evidence suggests that disruption to financial access was probably an important component in understanding the impact of the Great Depression on innovation. Our results highlight how variables that are more likely to capture a disruption to the local supply of capital explain the decline in innovation, while proxies that are more likely to capture economic distress more generally do not appear to have the same explanatory power. This interpretation is also consistent with several other results discussed later. For instance, we show that the long-run decline by independent is more extensive for technologies used in industries more dependent on external finance (Section 5.3).

Importantly, this result is also in line with an extensive body of historical evidence on the Great Depression. As discussed in Section (2), the shortage of risk capital has been generally seen as a key factor in explaining the difficulties of early-stage ventures during this period (e.g., [Kenney 2011](#)). Furthermore, the market for technologies during this period was already either national or, at the very least, regional (e.g., [Lamoreaux and Sokoloff 2001](#)), while funding networks were highly local. As a result, our empirical approach is more likely to capture differences in access to capital locally, rather than other mechanisms. Though certainly not conclusive, this body of evidence supports the idea that the presence of financial disruption may be crucial in understanding the reduction in innovation described in these analyses.

5.1.3 Robustness tests. Given the lack of differential trends in innovation prior to the Great Depression, the remaining omitted variable concern is that our county level treatment variable may be correlated with some other shock that (1) was contemporaneous to the Great Depression; (2) was correlated with how innovation changed around this period; and (3) was not caused by the Great Depression itself.

One possibility is that our proxies for a local shock to financial access could spuriously capture an omitted factor that is also correlated with local variation in exposure to national technological changes coincident with the Great Depression. For example, if some technologies experienced a much larger decline during the Great Depression and also tended to be produced in areas with bank distress, then counties producing those technologies might mechanically see a larger drop in innovation production. However, this channel is unlikely an important driving force behind our findings. First, in Table 3 we find that our crisis severity proxy does not predict any short-run changes in local patenting by firms, which also would have been exposed to the technological changes. Moreover, if local variation in exposure to national technology trends is relevant, then the results should disappear, or at least abate significantly after controlling for technology class-specific trends. In Table 5, we reshape our data at the county-by-time-by-technology class level and show that the results

Table 5
Local severity of the crisis during the Great Depression and independent innovation across technology classes

| | Ln(# Independent Patents+1) | | | | | | |
|--------------------------|-----------------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Crisis X After1929 | −0.140*** (0.016) | −0.140*** (0.016) | −0.142*** (0.025) | −0.156*** (0.027) | −0.151*** (0.023) | −0.148*** (0.025) | −0.101*** (0.019) |
| StateXTime FE | Y | Y | Y | Y | Y | Y | Y |
| County FE | Y | Y | Y | Y | Y | Y | Y |
| TechnologyXStateXTime FE | N | Y | N | N | N | N | N |
| Technology | All | All | A | B | E | F | G |
| Start Decade | 1910 | 1910 | 1910 | 1910 | 1910 | 1910 | 1910 |
| End Decade | 1940 | 1940 | 1940 | 1940 | 1940 | 1940 | 1940 |
| Adj R-Sq | 0.733 | 0.830 | 0.842 | 0.859 | 0.789 | 0.823 | 0.804 |
| Obs | 59,500 | 59,500 | 11,900 | 11,900 | 11,900 | 11,900 | 11,900 |

The table shows estimates from a difference-in-differences regression of the number of independent patents across technology classes on a proxy for the local severity of economic crisis during the Great Depression. The estimation strategy relies on cross-sectional variation in distress across U.S. counties within a state. The sample is the near universe of all independent patents granted by the U.S. Patent and Trademark Office (USPTO), that belong to the five most frequently patented technology classes, listed below. Independent denotes patents by inventors residing in the United States that were either unassigned or assigned to individuals at the time of the patent grant date. The unit of observation is county-decade-technology class in columns 1 and 2 and county-decade in columns 3–7 for the period 1910–1940. In columns 1–7, the dependent variable is the logarithm of one plus the number of independent patents. In columns 1 and 2, we count patents within each county-decade-technology class. In columns 3–7, we limit the sample to 5 most frequently patented technology classes by independent inventors in the 1920s: column 3, human necessities (CPC class A); column 4, performing operations or transporting (CPC class B); column 5, fixed constructions (CPC class E); column 6, mechanical engineering, lighting, heating, weapons, blasting engines, or pumps (CPC class F); and column 7, physics (CPC class G). *Crisis* is an indicator variable equal to one for counties with at least one bank suspension during the Great Depression years of 1930 through 1933, inclusive. The estimates of the effect of local distress on patents are the coefficients for the interaction between *Crisis* and the *After1929* indicator, which equals one for the observations starting from the 1930s decade. All columns include state-by-time and county fixed effects, while column 2 also includes technology class-by-state-by-time fixed effects. Standard errors are clustered at the county level and reported in parentheses.

* $p < .1$; ** $p < .05$; *** $p < .01$.

with technology-by-time fixed effects are still large and significant (column 2) and not different from the estimates at this level of aggregation without any of these additional fixed effects (column 1).³⁵ We also repeat the main specification separately for each of the top five largest independent inventor technology classes, as measured by the number of independent patents filed in the 1920s. Across all five, we find sizable, significant, and similar results (columns 3–7).

Another concern is that the response to the Great Depression may in part reflect other differences across distressed and nondistressed areas that might lead to differential trends in innovation following the Great Depression. To alleviate this concern, in Table A.3 we examine whether our findings are explained by observable differences in preshock county characteristics. In

³⁵ We use the main technology category, focusing on the five largest classes (i.e., human necessities, performing operations or transporting, fixed construction, mechanical engineering, lighting, heating, weapons, blasting engines or pumps, and physics). This classification is based on the letter component of the CPC for the patent. For less than 5% of patents we have more than one letter assigned per patent. For these few cases, we take the first listed (alphabetical order), but results are generally unaffected when using alternative approaches.

column 1, we show that the results still hold once we also control for the size of the population in 1920 interacted with a post-1929 dummy.³⁶ Similarly, the results are robust to controlling for a measure of the banking sector size at the county level (column 2) and for the pre-period share of population in manufacturing (column 3).

As an alternative way to deal with the heterogeneity between treatment and control counties, we also implement a matching estimator using a nearest-neighbor matching approach (Boucly, Sraer, and Thesmar 2011; Bernstein, Lerner, and Mezzanotti 2019). This approach allows us to deal with concerns about nonlinear effects of covariates acting as possible confounders. In particular, we start by considering all counties that did not experience financial distress during the depression. For each of these counties, we try to find any other county that experienced a bank suspension, where the following conditions also hold: (1) the county is in the same state; (2) population is within a 25% bandwidth around the unaffected county; or (3) independent innovation in the pre-period (the 1920s) is similar.³⁷ In Table A.4, we reestimate our main specification using this matched sample for independent patents (columns 1 and 2) and firm patents (columns 3 and 4). Overall, despite the reduction in sample size due to the matching, we replicate our key findings, in terms of economic and statistical significance.

One remaining concern is that reverse causality could be driving our findings if a sudden drop in patenting by independent inventors was actually the cause of bank suspensions in the aftermath of the Great Depression. We think this scenario is unlikely. First, R&D activity, especially when undertaken by independent inventors, was not heavily financed by banks during this period.³⁸ Second, we find no evidence of declines by firms, which are more likely to finance via bank lending and therefore are more subject to reverse causality concerns. Both of these findings suggest that reverse causality is unlikely to be the primary driver of our main findings.

³⁶ Along similar lines, one might be concerned from an external validity standpoint that our findings might be driven by variation among counties with only small levels of innovation. By contrast, in Appendix Table A.5 we show that findings are not statistically different in the largest (pre-Depression) innovation centers. This evidence is consistent with our general observations that the decline because of the Great Depression was also experienced in these larger innovation areas, albeit their decline is not much different than the average effect. In that respect, it seems plausible then that the sort of the findings we find for typical counties, are likely to also extend to innovation hubs as well.

³⁷ We divide counties into three groups: (1) no independent innovation (zero patents before); (2) moderate independent innovation (between zero and fifty patents); and (3) high independent innovation (above fifty patents). We then use this definition to match counties.

³⁸ Nanda and Nicholas (2014) provides evidence that R&D firms accounted for a small share of overall borrowing. More broadly, this discussion is related to the debate on the determinants of bank distress. To the extent that failures were driven by panics rather than weakness in the fundamentals (e.g., Friedman and Schwartz 1963), reverse causality should not be a concern. However, if distress is driven by a deterioration of the local demand for certain technologies (e.g., the sudden bankruptcy of a major firm that caused bank suspensions), then reverse causality could be a more serious concern. We believe that this concern may be fairly minor though in our specific setting. For instance, Calomiris and Mason (2003) find that lagged liabilities of failed companies do not explain bank failures.

Table 6
Local severity of the crisis during the Great Depression and independent innovation by inventor type

| | Ln(# Independent Patents+1) | | | |
|--------------------|-----------------------------|----------------------|----------------------|----------------------|
| | (1) | (2) | (3) | (4) |
| Crisis X After1929 | −0.071*** (0.022) | −0.134*** (0.027) | −0.068*** (0.026) | −0.158*** (0.026) |
| StateXTime FE | Y | Y | Y | Y |
| County FE | Y | Y | Y | Y |
| Inventor Type | Experienced | Inexperienced | Older | Younger |
| Start Decade | 1910 | 1910 | 1910 | 1910 |
| End Decade | 1940 | 1940 | 1940 | 1940 |
| Adj R-Sq | 0.818 | 0.872 | 0.838 | 0.836 |
| Obs | 11,900 | 11,900 | 11,900 | 11,900 |

The table shows estimates from a difference-in-differences regression of the number of patents filed by independent inventors on a proxy for the local severity of economic crisis during the Great Depression. Across different columns, we examine the effects across different types of inventors. The estimation strategy relies on cross-sectional variation in distress across U.S. counties within a state. The unit of observation is county-decade, for the period 1910–1940. In each column the outcome is the logarithm of one plus of the number of patents by independent inventors of the specific type who filed patents over 10-year periods within each county. In column 1, we look at patents filed by experienced inventors, while in column 2 we examine the number of patents filed by inexperienced inventors. We define experienced inventors as those who had received patents before, and inexperienced had no prior patents. In column 3, we look at patents filed by older inventors, while in column 4 we examine patents filed by younger inventors. The split between young and old inventors is done at the median of inventor age. *Crisis* is an indicator variable equal to one for counties with at least one bank suspension during the Great Depression years of 1930 through 1933, inclusive. The estimates of the effect of local distress on patents are the coefficients for the interaction between *Crisis* and the *After1929* indicator, which equals one for the observations starting from the 1930s decade. All columns include state-by-time and county fixed effects. Standard errors are clustered at the county level and reported in parentheses.

* $p < .1$; ** $p < .05$; *** $p < .01$.

5.1.4 The types of independent innovation most affected by the Great Depression. So far we find that the Great Depression led to a large and persistent decline in independent innovation. Next, we exploit our rich data to provide some novel insights on the distributional impact of this crisis on local innovation production. In addition to being able to evaluate the long-term quality of innovative output, our data allow us to obtain inventors’ demographic information from the census to examine which type of innovator was more affected by the shock. This represents a unique opportunity given how little is known about inventors in modern data.

We start by exploiting our inventor-census matched data and examine in Table 6 how our findings vary across different inventor groups that are likely to be differentially affected by the crisis. In particular, we find that the decline is larger among independent inventors who are inexperienced (columns 1 and 2), and younger (columns 3 and 4). The split between young and old inventors is done at the median of age, while experience sorts inventors between those with and without a previous patent. One way to interpret these findings is that these groups of inventors are less likely to be able to withstand severe duress. The affected inventors are less likely to have had social, reputational, or economic capital to buffer the economic crisis and therefore were less likely to be able to innovate on their own during the Great Depression.

Table 7
Local severity of the crisis during the Great Depression and quality of independent innovation

| | (1) Ind. # Cit | (2) Ind. Avg Citations | (3) Ind. Avg. Citations, CPC | (4) Ind. Avg. Citations (not logged) |
|--------------------|-------------------|------------------------------|------------------------------------|--|
| Crisis X After1929 | 0.013 (0.044) | 0.137*** (0.028) | 0.058*** (0.014) | 0.475*** (0.125) |
| StateXTime FE | Y | Y | Y | Y |
| County FE | Y | Y | Y | Y |
| Start Decade | 1910 | 1910 | 1910 | 1910 |
| End Decade | 1940 | 1940 | 1940 | 1940 |
| Adj R-Sq | 0.802 | 0.368 | 0.248 | 0.245 |
| Obs | 11,900 | 11,900 | 11,900 | 11,900 |

The table shows estimates from a difference-in-differences regression of independent patent quality metrics on the local severity of the economic crisis during the Great Depression. The estimation strategy relies on cross-sectional variation in distress across U.S. counties within a state. The sample is the near universe of all patents granted by the U.S. Patent and Trademark Office (USPTO) to either U.S. inventors or U.S. firms. The sample of future patent citations includes all patents granted by the USPTO, including independent, U.S. firm and non-U.S. patents. The unit of observation is county-decade, for the period 1910–1940. In column 1, the dependent variable is the logarithm of one plus the total number of future patent citations citing all independent patents filed over each 10-year period within a county. Independent denotes patents by inventors residing in the United States that were either unassigned or assigned to individuals at the time of the patent grant date. In column 2, we instead look at the (logarithm plus one) of the average number of citations received by independent patents. We then perform two robustness tests. In column 3, citations are adjusted by the average number of citations in the same technology class over the period of 1910–1940. The outcome is then log-transformed similar to the main analyses in column 2. In column 4, we use average citations without the log-transformation. *Crisis* is an indicator variable equal to one for counties with at least one bank suspension during the Great Depression years of 1930 through 1933, inclusive. The estimates of the effect of local distress on patents are the coefficients for the interaction between *Crisis* and the After1929 indicator, which equals one for the observations starting from the 1930s decade. All columns include state-by-time and county fixed effects. Standard errors are clustered at the county level and reported in parentheses.

* $p < .1$; ** $p < .05$; *** $p < .01$.

Another important dimension of heterogeneity is the quality of innovative output. A significant benefit of using patents is that we can also measure changes in innovation quality by looking at their impact on the future generations of innovations that cite them. Hence, we next examine the distributional effects of this decline specifically, whether the crisis displaced technological entrepreneurs that had high or low quality innovations. In principle, high-quality inventions may be better at withstanding a crisis. In fact, if the historical accounts are accurate that capital dry-up during the Great Depression played an important role in hurting independent innovation, and if capital did not dry out completely, the decline should affect relatively more inventions of lower quality, consistent with a traditional cleansing mechanism (Caballero and Hammour 1994). However, this intuition does not have to hold in practice because quality can be difficult to observe ex ante. For example, the crisis affected particular categories of inventors, for example, young or new inventors, who might lack reputation for producing high-quality innovations but who also may be better positioned to introduce newer (and potentially more impactful) ideas.

To examine this aspect of innovative activity, in column 1 of Table 7, we look at the total number of future citations received by patents filed in each county-decade as the outcome of interest. The same result is also presented

in Figure A.12. In stark contrast to our quantity results, we find essentially no differential changes in the future total citations given to independent inventor patents filed in more-distressed counties. These divergent results are explained by a relative increase in the average quality of patents filed in more severely affected areas (Figure A.13 and column 2 of Table 7). These results are similar when we adjust patent citations by technology classes and time (column 3). This evidence, combined with the decline in the quantity of innovation, potentially suggests that the drop in patenting by independent inventors might be in part driven by lower-quality projects. Consistent with this hypothesis, in Table A.6 we find that the drop in the quantity of patents is mostly driven by a decrease in the number of lower-citation patents, rather than a relative increase in highly cited patents.³⁹ Therefore, while technological entrepreneurs are forced to reduce their activity in response to the shock, independent inventors with high-quality ideas are still able to produce their inventions.

This evidence provides novel insights on the distributional effect of the Great Depression on independent inventors. In particular, we find that inventors who are less likely to withstand the crisis—because of a lack of social, reputational, or economic capital or because they were producing lower-quality or less-proven inventions—experienced a larger decline.

5.2 Great Depression accelerates the shift of innovation into large firms

After establishing that the Great Depression negatively affected the ability of independent inventors to produce innovation, we next examine whether this contraction in independent innovation was part of the broader acceleration of innovation into large firms. While in Table 3 we show that firm patenting did not change during the Great Depression, this null finding hides some heterogeneous responses by firms that were differentially affected by the crisis. In Table 8, we examine whether firm innovation responded differently for new versus incumbent firms and for small versus large incumbent firms. Younger and smaller firms are likely to have fewer resources to withstand a large economic shock. While being a larger or older firm could represent resilience to capital disruptions, it also would be consistent with higher resilience to economic shocks more generally, including any demand-side effects. Firms, and especially those that are larger and more established, may have been better able to compensate by producing multiple patents at a lower cost or switching to patents whose value remained high. We sort firms along these two dimensions based on firms' past patenting behavior and define new firms as those with

³⁹ In particular, we split patents into those that belong to the top 1% and the bottom 99% by the number of future citations, as well as top and bottom 10%/90% and 25%/75%, and we construct outcomes that are the (log-transformed) count of patents in each category at the county-decade level. Across these groups, we consistently find that the decline is always larger for lower quality patents, and in most cases we actually find that highly cited patents remain roughly constant. Furthermore, these results are presented controlling for population consistent with the robustness tests in prior analyses. However, without the population control, the effect is also significant for the top patents, suggesting that, at the margin, high-quality patents may have also suffered, though this bank distress-driven decline cannot be separated from the differential trends in large and smaller counties.

Table 8
Local severity of the crisis during the Great Depression and innovation by firm type

| | Ln(# Firm Patents+1) | | | |
|--------------------|----------------------|-------------------|-------------------|--------------------|
| | (1) | (2) | (3) | (4) |
| Crisis X After1929 | −0.034* (0.020) | 0.053* (0.028) | −0.001 (0.016) | 0.064** (0.027) |
| StateXTime FE | Y | Y | Y | Y |
| County FE | Y | Y | Y | Y |
| Firm Type | New | Incumbent | Small Incumbent | Large Incumbent |
| Start Decade | 1910 | 1910 | 1910 | 1910 |
| End Decade | 1940 | 1940 | 1940 | 1940 |
| Adj R-Sq | 0.845 | 0.883 | 0.796 | 0.874 |
| Obs | 11,900 | 11,900 | 11,900 | 11,900 |

The table shows estimates from a difference-in-differences regression of the number of patents by firm type on a proxy for the local severity of the economic crisis during the Great Depression. The estimation strategy relies on cross-sectional variation in distress across U.S. counties within a state. The unit of observation is county-decade, for the period 1910–1940. To start, we split firm patenting between new and incumbent firms, where new firms are those with no prior patents and incumbent firms are those with at least one prior patent. In column 1, we look at patents filed by new firms, and in column 2, we look at patenting by incumbent firms. In both cases, the outcome is the logarithm of one plus the number of firm patents in the firm category considered filed over 10-year periods in each county. We then focus on incumbent patents, and split this group based on firm size, proxied by the number of previous patenting. In particular, we define large incumbent firms as having at least three patents in a prior decade (three patents is the 75th percentile), and small firms are those with one or two patents in the prior decade. In column 3, the dependent variable is the logarithm of one plus the number of all patents filed by smaller incumbent firms over 10-year periods within each county. In column 4, the dependent variable is the logarithm of one plus the number of patents filed by larger incumbent firms over 10-year periods within each county. *Crisis* is an indicator variable equal to one for counties with at least one bank suspension during the Great Depression years of 1930 through 1933, inclusive. The estimates of the effect of local distress on patents are the coefficients for the interaction between *Crisis* and the *After1929* indicator, which equals one for the observations starting from the 1930s decade. All columns include state-by-time and county fixed effects. Standard errors are clustered at the county level and reported in parentheses. * $p < .1$; ** $p < .05$; *** $p < .01$.

no prior patents; large incumbent firms had at least three patents in a prior decade (three patents is the 75th percentile); and small incumbent firms are those with one or two patents in the prior decade.⁴⁰ Columns 1 and 2 show that, in the short run, new firms located in distressed counties experienced a 3.4% patenting decline, while incumbent firms’ patents actually increased by 5.3%. These results are consistent with the idea that new firms represent another measure of entrepreneurial activity. Moreover, columns 3 and 4 reveal that, among incumbent firms, larger firms saw a 6.4% increase in patents but there was no measurable change in patenting by smaller firms, suggesting that the increase in incumbent firm patents was driven by larger firms.⁴¹

⁴⁰ To validate this approach, we use the sample of patenting firms matched to Moody’s employed in Akkoyun and Ersahin (2020) and examine the patenting distribution within this sample of large companies. Consistent with the idea that large companies would be correctly categorized as such by looking at firms in the top quartile of the patenting distribution, we find that about 79% of the matched Moody’s sample of innovative companies had more than three patents during the decade 1909–1918. We thank the authors for kindly sharing the data.

⁴¹ One concern with this approach using only information about the size of the patent portfolio is that smaller, but highly innovative companies may be categorized as large, in part driving the differential response for this group. We address this issue in Appendix Table A.7. To start, we split large companies based on the number of inventors, and we find that our finding on large companies is mostly driven by companies with more inventors (column 2) rather few (column 1), suggesting that the actual size of the operation is important. Next, we specifically

Table 9
Local severity of the crisis during the Great Depression and large firm innovation by inventor type

| | Ln(# Firm Patents+1) | | | |
|--------------------|----------------------|---------------------|---------------------|---------------------|
| | (1) | (2) | (3) | (4) |
| Crisis X After1929 | 0.049** (0.021) | 0.059*** (0.020) | 0.052*** (0.020) | 0.074*** (0.021) |
| StateXTime FE | Y | Y | Y | Y |
| County FE | Y | Y | Y | Y |
| Inventor Type | Experienced | Inexperienced | Older | Younger |
| Start Decade | 1910 | 1910 | 1910 | 1910 |
| End Decade | 1940 | 1940 | 1940 | 1940 |
| Adj R-Sq | 0.842 | 0.869 | 0.846 | 0.844 |
| Obs | 11,900 | 11,900 | 11,900 | 11,900 |

The table shows estimates from a difference-in-differences regression of the number of patents filed by firms across different inventor types on a proxy for the local severity of economic crisis during the Great Depression. The estimation strategy relies on cross-sectional variation in distress across U.S. counties within a state. The unit of observation is county-decade, for the period 1910–1940. Across different columns, we examine the effects across different types of inventors, and in each column the outcome is the logarithm of one plus one the number of firm’s patents filed by an inventor that satisfies the specific characteristic during a 10-year period within each county. In column 1, we look at patents filed by experienced inventors, while in column 2 we examine the number of patents filed by inexperienced inventors. We define experienced inventors as those who had received patents before, and inexperienced as those with no prior patents. In column 3, we instead look at patents filed by older inventors, while in column 4 we examine patents filed by younger inventors. The split between young and old inventors is done at the median of inventor age. *Crisis* is an indicator variable equal to one for counties with at least one bank suspension during the Great Depression years of 1930 through 1933, inclusive. The estimates of the effect of local distress on patents are the coefficients for the interaction between *Crisis* and the *After1929* indicator, which equals one for the observations starting from the 1930s decade. All columns include state-by-time and county fixed effects. Standard errors are clustered at the county level and reported in parentheses.

* $p < .1$; ** $p < .05$; *** $p < .01$.

We show that large firms in distressed areas were not as affected by the crisis and, potentially, compensated in part for the decline in independent innovation, as well as document the tight connection between those independent inventors that see the largest innovation declines and the rise of large firm innovation. To examine this issue, we use our inventor-census matched data to measure how large firm innovation varied across different inventor types. Specifically, we replicate our main analysis focused on large, incumbent firms, but we now separately examine patenting based on the level of experience (columns 1 and 2) and age (columns 3 and 4) of inventors, as we did for independent inventors in Table 6. We find that the larger decline for independent inventors in these Groups (i.e., younger and inexperienced inventors) is mirrored by a larger increase in patenting among these two groups within large incumbent firms (Table 9). While suggestive, this evidence is consistent with a role of the Great Depression in reallocating human capital between different organizational forms of innovation, and, in particular, propelling actual and prospective independent inventors to join large firms. To examine this hypothesis more directly, we turn to our longitudinal inventor-level data to examine whether inventors who worked as independents in the precrisis period experienced a

look at a sample of companies that were extremely successful at patenting in the prior decade (more than eight patents) but only had one or two inventors (column 3). Consistent with our main interpretation, we find smaller and statistically insignificant results for these firms.

Table 10
Local severity of the crisis during the Great Depression and individual inventor patenting within firms during the 1930s

| | Patent in Firm in 1930s | | |
|-----------------|-------------------------|--------------------|--------------------|
| | (1) | (2) | (3) |
| Crisis | 0.020* (0.012) | 0.025** (0.012) | 0.024** (0.012) |
| State FE | Y | Y | Y |
| Patent Post | Y | Y | Y |
| Pre Ind Pat | Y | Y | Y |
| County Controls | N | Y | Y |
| Ind. Controls | N | N | Y |
| Adj R-Sq | 0.019 | 0.020 | 0.026 |
| Obs | 5,295 | 5,294 | 5,294 |

The table examines the potential reallocation of independent inventors into firms during the 1930s in counties that suffered more from the economic crisis during the Great Depression. The estimation strategy relies on cross-sectional variation in distress across U.S. counties within a state. To test for reallocation, we limit the sample to individual U.S. inventors who (1) we categorize as independent inventors during the 1920s (i.e., they have patented strictly more as independent than as inventor for a firm), and (2) had at least one patent during the 1930s; and (3) we could find in (at least) the 1920 census, which is the base year used for controls. Independents are patents by inventors residing in the United States that were either unassigned or assigned to individuals at the time of the patent grant date. The county-level variables (e.g., bank distress) are assigned based on their location in the 1930 census and, when this is not available, the location in the 1920 census. In all columns, the dependent variable equals 1 if the inventor obtained strictly more patents in the 1930s working for a firm versus as an independent inventor. Column 1 includes state fixed effects. Column 2 adds the additional county-level control (log of population in 1920), while column 3 adds a set of individual-level controls based on the 1920 census (homeownership, log of inventor age, status as an entrepreneur, and gender). *Crisis* is a dummy equal to one if bank distress in the county is above the median; this statistic is calculated using the final sample used in the analysis. Standard errors are clustered at the county level and reported in parentheses.

* $p < .1$; ** $p < .05$; *** $p < .01$.

higher probability of working for firms (versus staying independent) when living in counties with more distress.⁴² Indeed, in Table 10, we show that independent inventors operating in high-distress areas before the crisis were more likely to patent within firms following the Great Depression, and this effect is robust to a variety of robustness checks.⁴³

The evidence presented so far suggests that the economic crisis accelerated the process of shifting innovation into larger firms. In Table 11, we show that the acceleration of these national trends is even stronger over the long run. When we rerun our primary specification using a longer panel covering patents filed through the end of the twentieth century, we find that the decline in independent patenting persisted over time, but an increase in large firm patents partially offset this decline. The number of patents by large firms increased

⁴² In particular, this analysis focuses on inventors that (1) were matched to the 1920 Census; (2) were independent inventors in the 1920s; and (3) were still patenting in the 1930s. Using this sample of inventors, we then examine whether inventors living in a location with higher bank distress during the Depression (i.e., above the median) were more likely to be working for companies in the 1930s. This analysis aims to test whether the propensity to move between organizations was affected by the exposure to the crisis.

⁴³ We find consistent results if we only use a subsample of inventors who are less likely to be matched to wrong individuals in the census data sets (Table A.8 columns 3 and 4). Furthermore, in Table A.9, we conduct a placebo analysis by examining whether independent inventors in distressed counties also moved into firms more often before the 1930s, and we consistently find no effect in these placebo tests.

Table 11
Local severity of the crisis during the Great Depression and innovation quantity and quality in the (very) long run

| | (1) Ln(# Ind. Pat.+1) | (2) Ln(# Firm Pat.+1) | (3) Ln(# Cit. Ind.+1) | (4) Ln(# Cit. Firm+1) |
|--------------------|--------------------------|--------------------------|--------------------------|--------------------------|
| Crisis X After1929 | −0.196*** (0.030) | 0.179*** (0.039) | −0.052 (0.045) | 0.374*** (0.064) |
| StateXTime FE | Y | Y | Y | Y |
| County FE | Y | Y | Y | Y |
| Start Decade | 1910 | 1910 | 1910 | 1910 |
| End Decade | 1990 | 1990 | 1990 | 1990 |
| Adj R-Sq | 0.863 | 0.830 | 0.761 | 0.764 |
| Obs | 26,775 | 26,775 | 26,775 | 26,775 |

The table shows estimates from a difference-in-differences regression of the number of patents and patent citations on the local severity of economic crisis during the Great Depression in the (very) long run. The estimation strategy relies on cross-sectional variation in distress across U.S. counties within a state. The sample is the near universe of all patents granted by the U.S. Patent and Trademark Office (USPTO) to either U.S. inventors or U.S. firms. The unit of observation is county-decade, where decades include 1910 through 1990. In column 1, we limit the sample to independent patents and define the dependent variable as the logarithm of one plus the number of independent patents filed over 10-year periods within each county. Independent denotes patents by inventors residing in the United States that were either unassigned or assigned to individuals at the time of the patent grant date. In column 2, we limit the sample to patents assigned to large, incumbent U.S. firms and define the dependent variable as the logarithm of one plus the number of U.S. firm patents filed over 10-year periods within each county. We define large incumbent firms as having at least three patents in a prior decade (three patents is the 75th percentile). In columns 3 and 4, we repeat the same analyses, but we use as outcome variables the total number of all future citations given to patents filed by independents (column 3) and large firms (column 4) over 10-year periods within each county. *Crisis* is an indicator variable equal to one for counties with at least one bank suspension during the Great Depression years of 1930 through 1933, inclusive. The main coefficient of interest is the interaction between the *Crisis* variable and the After1929 indicator, which equals one for the observations starting from the 1930s decade. This variable estimates the average long-run change in the outcome considered between more and less affected areas. All columns include state-by-time and county fixed effects. Standard errors are clustered at the county level and reported in parentheses.

* $p < .1$; ** $p < .05$; *** $p < .01$.

in the long run, as did the quality of these patterns, as measured by total citations (column 4 of Table 11). These results suggest that, in the long run, firm innovation—even when adjusted for quality—went up in the areas harder-hit by the Great Depression, suggesting that firms benefited from the depression-propelled shift in innovation. In contrast, column 3 shows that the long-run changes in total citations given to independent patents were close to zero, consistent with the short-run null effects reported earlier in column 1 of Table 7 and with the decline mostly driven by low-quality innovations (Table A.6).

Overall, these results suggest that the local distress from the 1930s accelerated the shift of innovation into large, incumbent firms whose quality-adjusted output appears to also increase over the long run. Importantly, this evidence is not at odds with the decline in independent inventors being larger for lower-quality innovation and younger inventors. First, keeping constant the inherent talent of an inventor, her productivity can be quite different when working independently as opposed to within a firm. In particular, inventors that produced lower-quality innovation before the depression may be more successful when working in a larger organization. For example, firms might organize inventors to work in teams, which has become common over the past century (Bloom et al. 2020), and incentivize their workers to specialize

their expertise into narrower dimensions of the innovation process. Hence, the “total” of team innovation in firms might be larger than “the sum of its parts.” Second, our findings on the importance of younger inventors for the increase in innovation of larger firms suggest that firms might have benefited from the crop of newcomers to the innovation ecosystem as these newcomers might be less set in their ways and more open to experimentation, which is crucial in the innovation process (Braguinsky et al. 2021), and might be more attuned to technological changes and new productive tools useful for innovation.⁴⁴

Next, we explore different mechanisms that might explain such a hysteresis in the organization of innovation in the regions harder-hit by the Great Depression that we document so far.

5.3 Discussion on the long-run persistence of innovation changes

Our results show that the unfolding of the Great Depression—by reducing access to finance for technological entrepreneurs—led to a persistent decline in independent innovation and accelerated the rise of innovation produced by large firms. These results are consistent with theories where a severe crisis can aid an “equilibrium switch” and facilitate the transition of U.S. innovation from being entrepreneur-centric—where independent inventors are at the center of the innovation process—to more firm-centric. In principle, innovation can be either organized around firms or independent entrepreneurs, and each of these scenarios is a possible equilibrium, which is sustained by a whole ecosystem organized around it (Aghion and Tirole 1994; Gromb and Scharfstein 2002; Hellmann 2007; Ding and MacKay 2017).⁴⁵ Therefore, the transition between different equilibria is complicated because of the presence of externalities that generate hysteresis. Hence, while in aggregate, forces that have favored large firms over independent inventors in the long run were already pushing innovation toward firm-based production, the actual transition may take a long time to materialize. In this context, a deep economic crisis can lead to a dissolution of important aspects of the local ecosystems and therefore facilitate the transitions between possible equilibria.

A natural implication of this hypothesis is that we should expect the decline by independent inventors to be larger exactly where the incentive to shift into firms was larger. The intuition is that, once the economic shock removes some of the factors constraining this reallocation, the decline should be more extensive where independent inventors appear to face a larger disadvantage relative to firms. Following the literature, we argue that firms’

⁴⁴ For example, recent evidence by Babina et al. (2020a) shows that incumbent U.S. firms that had access to AI-trained students via alumni networks of universities that had strong AI research prior to the increase in commercial interest in AI in 2012 have benefited dramatically in terms of faster growth from hiring these AI-trained students and using AI technologies for increased product innovation.

⁴⁵ While many regions in the United States would like to develop into the Silicon Valley, perhaps not surprisingly, moving to an equilibrium where the local environment supports that sort of technological entrepreneurial activity is not trivial (Kerr and Robert-Nicoud 2020).

increasing comparative advantage was in part explained by their advantage in managing technologies that were becoming more capital intensive and complex (Teece David 1988; Hughes 2004; Lamoreaux and Sokoloff 2005). We test this idea by exploring whether the long-run decline in independent patents is larger along these dimensions.

First, large, established firms have a natural advantage at raising capital and are likely to be less reliant on local funding networks for innovation, which we can think of as “agglomerations” of capital and innovation intermediation. A large economic crisis can lead to a dissolution of important aspects of the local ecosystems, such as funding networks, and therefore permanently disrupt the flows of information between the suppliers of risky capital and its potential users, namely, technological entrepreneurs. Consistent with this narrative, in Section 5.1, we find that independent inventors who are more likely to be subject to these information asymmetries and suffer from the disruption of local networks, specifically younger and inexperienced independent inventors, see larger declines. Moreover, we expect the decline in independent patenting to be larger for those technologies that are used in industries that are more dependent on external financing (Rajan and Zingales 1998; Nanda and Nicholas 2014). Indeed, in the long run, the decline in independent innovation was significantly larger for technologies used in industries that are more dependent on external financing (columns 1 and 2, in Table 12). This evidence is also consistent with our interpretation of our results as largely capturing a reduction in financial access for technological entrepreneurs in a local area. It is worth noting, however, that such findings do not preclude the possibility that younger and inexperienced independent inventors and those in externally finance dependent industries also might be less able to withstand the more general economic shocks occurring at this time, including those driven by local demand.

Second, firms also should be better at managing increasingly complex technologies that require growing specialization in innovation production and working in teams. Hence, the decline in independent innovation could be larger for those inventors who are unable to successfully operate in teams and, consequently cannot compete effectively with firms in this dimension. Our results are consistent with this hypothesis: while we find a decline in areas harder-hit by the crisis in both groups—in solo-inventor and team-inventor independent patents (columns 3 and 4 of Table 12)—the drop is twice as large for solo patents.

Altogether, the evidence is consistent with the idea that the decline in independent inventors and the corresponding rise of innovation in large firms could be explained in the context of an equilibria shift accelerated by the crisis. However, these results do not necessarily exclude that other mechanisms could have also played some role in this process. To conclude this section, without claiming to be exhaustive, we discuss several of these additional mechanisms.

One alternative factor that could potentially explain our findings is an increase in government intervention in innovative activity following the Great

Table 12
Local severity of the crisis during the Great Depression and independent innovation in the (very) long run: Heterogeneity by external finance dependence and teamwork

| | Ln(# Independent Patents+1) | | | |
|--------------------|-----------------------------|----------------------|----------------------|----------------------|
| | (1) | (2) | (3) | (4) |
| Crisis X After1929 | -0.216*** (0.029) | -0.142*** (0.026) | -0.201*** (0.030) | -0.109*** (0.023) |
| StateXTime FE | Y | Y | Y | Y |
| County FE | Y | Y | Y | Y |
| LHS | High Fin. Dep. | Low Fin. Dep. | Solo Patent | Team Patent |
| Start Decade | 1910 | 1910 | 1910 | 1910 |
| End Decade | 1940 | 1940 | 1940 | 1940 |
| Adj R-Sq | 0.849 | 0.831 | 0.860 | 0.772 |
| Obs | 26,775 | 26,775 | 26,775 | 26,775 |

The table shows estimates from a difference-in-differences regression of the number of patents on the local severity of economic crisis during the Great Depression in the (very) long run across different patent types. The estimation strategy relies on cross-sectional variation in distress across U.S. counties within a state. The sample is the near universe of all patents granted by the U.S. Patent and Trademark Office (USPTO) to either U.S. inventors or U.S. firms. The unit of observation is county-decade, where decades include 1910 through 1990. In column 1, we limit the sample to independent patents in technologies used by industries that are more dependent on external finance and define the dependent variable as the logarithm of one plus the number of independent patents in this category filed over 10-year periods within each county. We identify a patent as high-dependence if its technology class (CPC three-digit) is linked with any high-dependence industry (column 3, table A3) in Nanda and Nicholas (2014). We use the concordance table by Goldschlag et al. (2019) to link industries and technologies. In column 2, we repeat the same procedure but now look at independent patents in technologies that are used in industries less dependent on external finance, defined as the residual category. In column 3, we limit the sample to independent patents that are produced by inventors working alone (i.e., solo inventor) and define the dependent variable as the logarithm of one plus the number of independent patents in this category filed over 10-year periods within each county. Following the same logic, in column 4, we do the same but focus on patents filed by independent inventors patenting in teams. *Crisis* is an indicator variable equal to one for counties with at least one bank suspension during the Great Depression years of 1930 through 1933, inclusive. The main coefficient of interest is the interaction between the *Crisis* variable and the After1929 indicator, which equals one for the observations starting from the 1930s decade. This variable estimates the average long-run change in the outcome considered between more- and less-affected areas. All columns include state-by-time and county fixed effects. Standard errors are clustered at the county level and reported in parentheses.

* $p < .1$; ** $p < .05$; *** $p < .01$.

Depression. Starting with the New Deal, the U.S. government increased its role in the economy, in terms of both the size of its budget and entering into new areas of the economy. In this context, some scholars have argued that this paradigm shift in government policy may have favored large, incumbent firms, which may be better positioned to work with the government, at the expense of smaller players (Blum 1976; Vatter 1985; Mowery and Rosenberg 1991). This hypothesis may be particularly relevant in the long run, because starting in the 1940s the U.S. government also started to play an increasingly important role in innovation (e.g., Nicholas 2019; Gross and Sampat 2020). However, in Table A.10, we find that the long-run decline in independent patenting is not driven by those technologies that experienced increasing government interest over the long run: the decline is actually larger for technologies with lower government interest.⁴⁶

⁴⁶ We examine this issue by splitting patents between technologies with high versus low government involvement using two methodologies. First, we rely on Gross and Sampat (2020) and define as high government involvement

Another possibility is that harder-hit counties might have seen an increased out-migration of inventors following the Great Depression, which might have disrupted local labor markets and knowledge spillovers. A large, recent literature in economic history highlights the importance of migration to understand the effect of the Great Depression in the American economy (e.g., [Feigenbaum 2015](#)). Given that the local entrepreneurial ecosystem was, and still is, highly dependent on knowledge spillovers via local networks of innovators and entrepreneurs, the departures might have been particularly costly for independent inventors, making large firms a more attractive places to innovate. From our inventor-census matched data, we use the inventor location data over time from the censuses to test this hypothesis empirically. In [Table A.11](#), we find no evidence that inventors were keen to migrate out of distressed counties following the Great Depression. This null result of local distress on inventor geographic mobility, coupled with the increased mobility of independent inventors into firms, suggests that obtaining paid employment may have been preferable to bearing the costs of geographic reallocation. This null result also suggests that the out-migration channel may not play a significant role in explaining our findings.

While definitively proving the driver of our observed innovation hysteresis is unlikely, overall, the evidence in this section is consistent with the idea that large shocks can accelerate an equilibria shift in the organization of innovation: the deteriorating environment for entrepreneurs in the 1930s accelerated the process of shifting innovation into larger firms, which were better positioned over the long run to access capital to finance ever more technologically complex and capital-intensive technologies.

6. Conclusion

Using a difference-in-differences design comparing counties that were more exposed to duress during the Great Depression to counties less affected, we document an important role of the Great Depression in triggering a large, sudden, and persistent reduction in local patents filed by the largest group of innovators of that period, namely, independent inventors. This decline was especially prevalent among young and inexperienced inventors and lower-quality inventions. Furthermore, we find evidence that the reduction in access to finance likely played a significant role in the observed effects. In the long run, independent patents declined more in technologies used in industries more dependent on external finance and produced by solo inventors as opposed to patents created by teams of inventors. In contrast, on average, firms had no

as those technologies that were part of the research programs supported by Office of Scientific Research and Development during WWII, and all as others are defined as low government involvement. Second, we identify a technology as high government involvement as those technologies that are above the median of share of patents assigned to the U.S. government.

innovation declines, and innovation even rose in incumbent, large firms in areas harder-hit by the Great Depression. This increase in large firm innovation was bigger for the same inventor types who saw a greater decrease in independent innovation. The importance of independent inventors was already falling at the national level, which when combined with the rest of our findings may suggest that the crisis accelerated these trends in some regions, driven by growing firm advantages from economies of scale for raising capital and managing increasingly complex technologies.

The Great Depression provides a useful laboratory to study the role of crises in shaping innovation. In fact, our results highlight how crises may act as catalyst for deep changes in the way innovation is organized and conducted. By leading to the dissolution of important aspects of the status quo, a disruption to capital access can facilitate transitions between different ways in which innovation is organized and technology is employed, potentially accelerating some of the existing trends that are already present in the economy. In our specific context, we show that the Great Depression may have facilitated the shift of U.S. innovation from being entrepreneur-centric—where independent inventors are at the center of the innovation process—to more firm-centric. This process interacted with some of the underlying technology and business forces that were already improving the competitive position of firms relative to independent inventors (Teece David 1988; Hughes 2004; Lamoreaux and Sokoloff 2005).

Furthermore, our evidence also can be thought of as a cautionary tale when examining the impact of shocks on innovation. In fact, our findings highlight that to truly understand the impact of a large crisis, it is crucial to examine the effect on the overall innovation ecosystem. While most past work focuses on the impact on either incumbent firms or startups separately, our new comprehensive patent data allow us to show a dynamic connection between innovation by technological entrepreneurs and incumbent firms in response to a crisis. In general, sufficiently large shocks—on top of having a direct effect on one group of innovators—can also lead to a reallocation across more and less affected organizational forms and groups. At the same time, to the extent that the shock actually induces a cleansing effect (Caballero and Hammour 1994), the overall effect on technological progress could be substantially lower or might even be positive. Our findings suggest that accounting for the redistribution of innovation, especially cross-organizationally, is likely to be critical in understanding the overall effects on innovation and growth in the aftermath of an economic crisis.

References

- Abramitzky, R., L. Boustan, J. Feigenbaum, K. Eriksson, and S. Perez. 2021. Automated linking of historical data. *Journal of Economic Literature* 59:865–918.
- Abramitzky, R., R. Mill, and S. Perez. 2019. Linking individuals across historical sources: A fully automated approach. *Historical Methods: A Journal of Quantitative and Interdisciplinary History* 53:94–111.

- Aghion, P., N. Bloom, R. Blundell, R. Griffith, and P. Howitt. 2005. Competition and innovation: An inverted-u relationship. *Quarterly Journal of Economics* 120:701–28.
- Aghion, P., and J. Tirole. 1994. The management of innovation. *Quarterly Journal of Economics* 109:1185–209.
- Akcigit, U., J. Grigsby, and T. Nicholas. 2017. The rise of American Ingenuity: Innovation and inventors of the Golden Age. Working Paper, Harvard Business School.
- Akkoyun, C., and N. Ersahin. 2020. When does information disclosure help innovation? evidence from blue sky laws. *Evidence from Blue Sky Laws* (April 6, 2020) .
- Akkoyun, H. C. 2018. Investor protection and financing innovation: Evidence from blue sky laws .
- Ante, S. E. 2008. *Creative capital: Georges doriot and the birth of venture capital*. Cambridge, MA: Harvard Business Press.
- Arora, A., S. Belenzon, K. Kosenko, J. Suh, and Y. Yafeh. 2021. The rise of scientific research in corporate america. Working Paper, Duke University.
- Babina, T. 2020. Destructive creation at work: How financial distress spurs entrepreneurship. *Review of Financial Studies* 33:4061–101.
- Babina, T., A. Fedyk, A. X. He, and J. Hodson. 2020a. Artificial intelligence, firm growth, and industry concentration. *Firm Growth, and Industry Concentration* (July 14, 2020) .
- Babina, T., D. Garcia, and G. A. Tate. 2017. Friends during hard times: evidence from the great depression. *Research Paper, Columbia Business School* .
- Babina, T., A. X. He, S. T. Howell, E. R. Perlman, and J. Staudt. 2020b. The color of money: Federal vs. industry funding of university research. Working Paper, Columbia University.
- Babina, T., and S. T. Howell. 2018. Entrepreneurial spillovers from corporate r&d. Working Paper, Columbia University.
- Babina, T., P. Ouimet, and R. Zarutskie. 2020. Ips, human capital, and labor reallocation. Working Paper, Columbia University.
- Bai, J., D. Carvalho, and G. M. Phillips. 2018. The impact of bank credit on labor reallocation and aggregate industry productivity. *Journal of Finance* 73:2787–836.
- Beauchamp, C. 2015. The first patent litigation explosion. *Yale Law Journal* .
- Bell, A., R. Chetty, X. Jaravel, N. Petkova, and J. Van Reenen. 2019. Who becomes an inventor in america? the importance of exposure to innovation. *Quarterly Journal of Economics* 134:647–713.
- Benmelech, E., C. Frydman, and D. Papanikolaou. 2019. Financial Frictions and Employment during the Great Depression. *Journal of Financial Economics* 133:541–63.
- Berkes, E. 2018. Comprehensive Universe of U.S. Patents (CUSP): Data and facts. Working Paper, Ohio State University.
- Bernanke, B. S. 1983. Nonmonetary effects of the financial crisis in the propagation of the Great Depression. *American Economic Review* 73:257–76.
- Bernstein, S., J. Lerner, and F. Mezzanotti. 2019. Private equity and financial fragility during the crisis. *Review of Financial Studies* 32:1309–73.
- Bernstein, S., T. McQuade, and R. R. Townsend. 2021. Do household wealth shocks affect productivity? evidence from innovative workers during the great recession. *Journal of Finance* 76:57–111.
- Bernstein, S., R. R. Townsend, and T. Xu. 2020. Flight to safety: How economic downturns affect talent flows to startups. Working Paper, Harvard University.
- Bertrand, M., E. Duflo, and S. Mullainathan. 2004. How much should we trust differences-in-differences estimates? *Quarterly Journal of Economics* 119:249–75.

- Bloom, N., C. I. Jones, J. Van Reenen, and M. Webb. 2020. Are ideas getting harder to find? *American Economic Review* 110:1104–44.
- Blum, J. M. 1976. *V was for victory: Politics and american culture during world war ii*. New York: Houghton Mifflin Harcourt.
- Boucly, Q., D. Sraer, and D. Thesmar. 2011. Growth lboos. *Journal of Financial Economics* 102:432–53.
- Boustan, L. P., P. V. Fishback, and S. Kantor. 2010. The effect of internal migration on local labor markets: American cities during the great depression. *Journal of Labor Economics* 28:719–46.
- Braguinsky, S., A. Ohyama, T. Okazaki, and C. Syverson. 2021. Product innovation, product diversification, and firm growth: Evidence from japan's early industrialization. *American Economic Review* 111:3795–826.
- Caballero, R. J., and M. L. Hammour. 1994. The cleansing effect of recessions. *American Economic Review* 84:1350–68.
- Calomiris, C. W., and J. Mason. 1997. Contagion and bank failures during the great depression: The june 1932 chicago banking panic. *American Economic Review* 87:863–83.
- Calomiris, C. W., and J. R. Mason. 2003. Fundamentals, panics, and bank distress during the Depression. *American Economic Review* 93:1615–47.
- Cerra, V., and S. Saxena. 2008. Growth dynamics: The myth of economic recovery. *American Economic Review* 98:439–57.
- Coase, R. H. 1937. The nature of the firm. *Economica* 4:386–405.
- Cole, H. L., and L. E. Ohanian. 2007. A second look at the us great depression from a neoclassical perspective. *Great depressions of the twentieth century*. Minneapolis: Federal Reserve Bank of Minneapolis 21–58.
- De Rassenfosse, G., and B. van Pottelsberghe de la Potterie. 2013. The role of fees in patent systems: Theory and evidence. *Journal of Economic Surveys* 27:696–716.
- Decker, R., J. Haltiwanger, R. Jarmin, and J. Miranda. 2014. The role of entrepreneurship in us job creation and economic dynamism. *Journal of Economic Perspectives* 28:3–24.
- Ding, F., and P. MacKay. 2017. Organizing innovation. Working Paper.
- Duval, R., G. H. Hong, and Y. Timmer. 2020. Financial frictions and the great productivity slowdown. *Review of Financial Studies* 33:475–503.
- Eichengreen, B. 2004. Understanding the great depression. *Canadian Journal of Economics/Revue canadienne d'Economie* 37:1–27.
- Feigenbaum, J. J. 2015. Intergenerational mobility during the great depression. Working Paper, Harvard University.
- Field, A. J. 2003. The most technologically progressive decade of the century. *American Economic Review* 93:1399–413.
- Fishback, P. V., W. C. Horrace, and S. Kantor. 2001. The impact of new deal expenditures on local economic activity: An examination of retail sales, 1929–1939. Working Paper, University of Arizona.
- Fishback, P. V., S. Kantor, and J. J. Wallis. 2003. Can the new deal's three rs be rehabilitated? a program-by-program, county-by-county analysis. *Explorations in Economic History* 40:278–307.
- Frésard, L., G. Hoberg, and G. M. Phillips. 2020. Innovation activities and integration through vertical acquisitions. *Review of Financial Studies* 33:2937–76.
- Friedman, M., and A. J. Schwartz. 1963. *A monetary history of the us 1867–1960*. Princeton, NJ: Princeton University Press.
- Gompers, P., J. Lerner, and D. Scharfstein. 2005. Entrepreneurial spawning: Public corporations and the genesis of new ventures, 1986 to 1999. *Journal of Finance* 60:577–614.

- Gompers, P. A., W. Gornall, S. N. Kaplan, and I. A. Strebulaev. 2020. How do venture capitalists make decisions? *Journal of Financial Economics* 135:169–90.
- Gordon, R. J. 1999. Us economic growth since 1870: one big wave? *American Economic Review* 89:123–8.
- Gorton, G., T. Laarits, and T. Muir. 2019. 1930: First modern crisis. Working Paper, Yale University.
- Gorton, G., and A. Metrick. 2013. The federal reserve and panic prevention: The roles of financial regulation and lender of last resort. *Journal of Economic Perspectives* 27:45–64.
- Gourio, F., T. Messer, and M. Siemer. 2016. Firm Entry and Macroeconomic Dynamics: A State-Level Analysis. *American Economic Review* 106:214–8.
- Gromb, D., and D. Scharfstein. 2002. Entrepreneurship in equilibrium. Working Paper, INSEAD.
- Gross, D. P., and B. N. Sampat. 2020. Inventing the endless frontier: The effects of the world war ii research effort on post-war innovation. Working Paper, Harvard University.
- Guglielmo, M. 1998. *What caused chicago bank failures in the great depression? a look at the 1920s*. Ph.D. Thesis, Cambridge University Press.
- Hall, B. H., A. B. Jaffe, and M. Trajtenberg. 2001. The nber patent citation data file: Lessons, insights and methodological tools. Working Paper, University of California, Berkeley.
- Hall, B. H., and J. Lerner. 2010. The financing of r&d and innovation. In *Handbook of the economics of innovation*, vol. 1, 609–39. Amsterdam, the Netherlands: Elsevier.
- Hall, R. E. 2015. Quantifying the lasting harm to the us economy from the financial crisis. *NBER Macroeconomics Annual* 29:71–128.
- Hart, O. D. 1988. Incomplete contracts and the theory of the firm. *Journal of Law Economics & Organisation* 4:119–39.
- Hellmann, T. 2007. When do employees become entrepreneurs? *Management Science* 53:919–33.
- Huber, K. 2018. Disentangling the effects of a banking crisis: evidence from german firms and counties. *American Economic Review* 108:868–98.
- Hughes, T. P. 2004. *American genesis: a century of invention and technological enthusiasm, 1870-1970*. Chicago: University of Chicago Press.
- Inderst, R., and H. M. Muller. 2004. The effect of capital market characteristics on the value of start-up firms. *Journal of Financial Economics* 72:319–56.
- Jacoby, N. H., and R. J. Saulnier. 1947. Business finance and banking. In *Business Finance and Banking*, 221–30. NBER.
- Jaffe, A. B., and M. Trajtenberg. 2002. *Patents, citations, and innovations: A window on the knowledge economy*. Cambridge, MA: MIT Press.
- James, M., and B. R. James. 1954. *Biography of a bank: the story of bank of america nt and sa*. New York: Harper.
- Kelly, B., D. Papanikolaou, A. Seru, and M. Taddy. 2018. Measuring technological innovation over the long run. Working Paper, Yale University.
- Kenney, M. 2011. How venture capital became a component of the us national system of innovation. *Industrial and Corporate Change* 20:1677–723.
- Kerr, S. P., and W. R. Kerr. 2020. Immigration policy levers for us innovation and startups. Working Paper, Wellesley College.
- Kerr, W. R., J. Lerner, and A. Schoar. 2011. The consequences of entrepreneurial finance: Evidence from angel financings. *Review of Financial Studies* 27:20–55.

- Kerr, W. R., and W. F. Lincoln. 2010. The supply side of innovation: H-1b visa reforms and us ethnic invention. *Journal of Labor Economics* 28:473–508.
- Kerr, W. R., and F. Robert-Nicoud. 2020. Tech clusters. *Journal of Economic Perspectives* 34:50–76.
- Lamoreaux, N. R., and M. Levenstein. 2014. Patenting in an entrepreneurial region during the great depression: The case of cleveland, ohio. Working Paper, Yale University.
- Lamoreaux, N. R., M. Levenstein, and K. L. Sokoloff. 2006. Mobilizing venture capital during the second industrial revolution: Cleveland, ohio, 1870-1920. Working Paper, Yale University.
- . 2007. Do innovative regions inevitably decline? lessons from cleveland’s experience in the 1920s. In *Business History Conference. Business and Economic History On-line: Papers Presented at the BHC Annual Meeting*, vol. 5, 1. Business History Conference.
- Lamoreaux, N. R., and K. L. Sokoloff. 1999. Inventors, firms, and the market for technology in the late nineteenth and early twentieth centuries. In *Learning by doing in markets, firms, and countries*, 19–60. Chicago: University of Chicago Press.
- . 2001. Market trade in patents and the rise of a class of specialized inventors in the 19th-century United States. *American Economic Review* 91:39–44.
- . 2005. The decline of the independent inventor: A Schumpeterian story? Working Paper, Yale University.
- Lamoreaux, N. R., K. L. Sokoloff, and D. Sutthiphisal. 2009. The reorganization of inventive activity in the United States during the early twentieth century. Working Paper, Yale University.
- Landes, D. S., J. Mokyr, and W. J. Baumol. 2012. *The invention of enterprise: Entrepreneurship from ancient mesopotamia to modern times*. Princeton, NJ: Princeton University Press.
- Lee, J., and F. Mezzanotti. 2017. Bank distress and manufacturing: Evidence from the Great Depression. Working Paper, Harvard University.
- Li, G.-C., R. Lai, A. D’Amour, D. M. Doolin, Y. Sun, V. I. Torvik, Z. Y. Amy, and L. Fleming. 2014. Disambiguation and co-authorship networks of the us patent inventor database (1975–2010). *Research Policy* 43:941–55.
- Long, J., and J. Ferrie. 2013. Intergenerational occupational mobility in great britain and the united states since 1850. *American Economic Review* 103:1109–37.
- Manso, G., B. Balsmeier, and L. Fleming. 2019. Heterogeneous innovation and the antifragile economy. Working Paper, University of California, Berkeley.
- Margo, R. A. 1993. Employment and unemployment in the 1930s. *Journal of Economic Perspectives* 7:41–59.
- Mezzanotti, F. 2020. Roadblock to innovation: The role of patent litigation in corporate r&d. *Management Science* 67:7362–90.
- Mezzanotti, F., and T. Simcoe. 2019. Patent policy and american innovation after ebay: An empirical examination. *Research Policy* 48:1271–81.
- Mitchener, K., and G. Richardson. 2019. Network contagion and interbank amplification during the great depression. *Journal of Political Economy* 127:465–507.
- Mitchener, K. J., and G. Richardson. 2020. Contagion of fear. Working Paper, Santa Clara University.
- Moretti, E., C. Steinwender, and J. Van Reenen. 2019. The intellectual spoils of war? defense r&d, productivity and international spillovers. Working Paper, University of California, Berkeley.
- Moser, P. 2005. How do patent laws influence innovation? evidence from nineteenth-century world’s fairs. *American Economic Review* 95:1214–36.
- Moser, P., A. Voena, and F. Waldinger. 2014. German jewish émigrés and us invention. *American Economic Review* 104:3222–55.

- Mowery, D. C., and N. Rosenberg. 1991. *Technology and the pursuit of economic growth*. Cambridge, UK: Cambridge University Press.
- Nanda, R., and T. Nicholas. 2014. Did bank distress stifle innovation during the Great Depression? *Journal of Financial Economics* 114:273–92.
- Nanda, R., and J. B. Sørensen. 2010. Workplace peers and entrepreneurship. *Management Science* 56:1116–26.
- Nicholas, T. 2008. Does innovation cause stock market runups? evidence from the great crash. *American Economic Review* 98:1370–96.
- . 2010. The role of independent invention in US technological development, 1880–1930. *The Journal of Economic History* 70:57–82.
- . 2019. *Vc: An american history*. Cambridge, MA: Harvard University Press.
- Olney, M. L. 1999. Avoiding default: The role of credit in the consumption collapse of 1930. *Quarterly Journal of Economics* 114:319–35.
- Postel-Vinay, N. 2016. What caused chicao bank failures in the great depression? a look at the 1920s. *Journal of Economic History* 76:478–519.
- Quincy, S. 2019. 'loans for the little fellow': credit, crisis, and recovery in the great depression. Working Paper, Vanderbilt University.
- Rajan, R., and R. Ramcharan. 2015. The anatomy of a credit crisis: The boom and bust in farm land prices in the United States in the 1920s. *American Economic Review* 105:1439–77.
- Rajan, R. G., and L. Zingales. 1998. Financial dependence and growth. *American Economic Review* 88:559–86.
- Reinhart, C., and K. Rogoff. 2009. The aftermath of financial crises. *American Economic Review: Papers and Proceedings* 99:466–72.
- Richardson, G. 2007. Categories and causes of bank distress during the great depression, 1929–1933: The illiquidity versus insolvency debate revisited. *Explorations in Economic History* 44:588–607.
- Richardson, G., and W. Troost. 2009. Monetary intervention mitigated banking panics during the great depression: quasi-experimental evidence from a federal reserve district border, 1929–1933. *Journal of Political Economy* 117:1031–73.
- Romer, C. D. 1993. The nation in depression. *Journal of Economic Perspectives* 7:19–39.
- Sarada, S., M. J. Andrews, and N. L. Ziebarth. 2019. Changes in the demographics of american inventors, 1870–1940. *Explorations in Economic History* 74:101275–.
- Schumpeter, J. A. 1934. Depressions. can we learn from past experience. In J. Schumpeter, ed., *The economics of the recovery program*. New York: McGraw-Hill.
- . 1942. *Capitalism, socialism, and democracy*. New York: Harper.
- Seru, A. 2014. Firm boundaries matter: Evidence from conglomerates and r&d activity. *Journal of Financial Economics* 111:381–405.
- Shane, S. 2008. *Fool's gold?: The truth behind angel investing in america*. Oxford, UK: Oxford University Press.
- Teece David, J. 1988. Technological change and the nature of the firm. *Giovanni Dosi* .
- Temin, P. 1976. *Did monetary forces cause the great depression?* New York: Norton.
- Vatter, H. G. 1985. *The us economy in world war ii*. New York: Columbia University Press.
- Ziebarth, N. 2013. Identifying the effects of bank failures from a natural experiment in Mississippi during the Great Depression. *American Economic Journal: Macroeconomics* 5:81–101.