Do Minimum Wage Hikes Hinder Entrepreneurship?*

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Abstract

I address two new questions: Do minimum wage hikes lower the survival rates of startups (firms of age one year)? Do minimum wage hikes lower the conditional survival rates of young firms (ages two to five years)? Relying on a novel panel data set that characterizes the count of continuing and dead private firms, I find that minimum wage hikes lower startup survival rates. Further, the conditional survival rates among firms of age two are less adversely affected, whereas firms of ages three, four, and five are not affected. Debates concerning minimum wage policies can benefit from my entrepreneurship perspectives.

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Minimum wages set to increase in many states in 2017. About 4.3 million low-wage workers across the country are slated to receive a raise. –Wall Street Journal, December 30, 2016

1. Introduction

In this paper, I investigate an important real-world question: Do minimum wage hikes stifle entrepreneurship? Its relevance is rooted in the transformational role that entrepreneurship plays in the economy.[1] At the same time, an answer is also critical amid the long-standing and still ongoing debate of minimum wage policies. Stakeholders in the debate include enterpreneurs, labor unions, politicians, low-skilled workers, business advocates, activists, and the media.

Uniquely important in addressing my core questions, the constructed panel data offers annual counts of continuing and dead firms of ages one through five years, and has encompassed 50 U.S. states and the District of Columbia for over 33 years. My headline conclusions are (i) that minimum wage hikes are associated with lower startup survival rates (firms of age one year) and this effect is statistically significant, and (ii) the negative effect of minimum wage hikes on the conditional survival rates attenuates among firms of age two years, and becomes statistically insignificant among firms of ages three to five years. These empirical results have not been established and can provide a basis for informed conversations about the social costs and benefits of minimum wage policies at all levels of the political bloodstream.

Startups and young firms dominate job creation and growth among small firms, whereby small firms employ more than half of private-sector employees and generate more than half of new jobs (e.g., Haltiwanger, Jarmin, and Miranda (2013)). They are often viewed as propellers of new technologies and innovations. Thus, the question of how minimum wage hikes influence the

[1] Entrepreneurship is a driving engine of growth, job creation, and innovation in the economy, which traverses both low- and high-technology enterprises. This phenomena is exemplified in the story of the entrepreneur, Kevin Plank, who created the athletic gear producer Under Armor. While it started with a few employees and $17,000 in sales in 1996, the company grew to have 5,800 full-time employees and generated $3.9 billion in revenue in 2015.

vulnerabilities of entrepreneurship merits attention and is at the heart of my paper.

The minimum wage policy has been controversial and peppered with inquiries since its inception. Opponents of minimum wage hikes feature heartbreaking stories of closed-down local businesses and lost jobs (see www.facesof15.com as an example). Business advocate organizations, such as the National Small Business Association (NSBA) and the National Federation of Independent Business, actively lobby against minimum wage increases. A recent report by NSBA quantified this effect: a 5% increase in the minimum wage can translate into a 2.5% loss of minimum wage jobs, and this exposure is concentrated among small businesses (http://www.nsba.biz/wp-content/uploads/2012/05/Minimum-Wage.pdf).

On the other hand, many supporters, including unions and legislative bodies, are equally entrenched in their view that higher minimum wages benefit everyone, including *both* workers and business owners. For example, the U.S. Department of Labor features "Minimum Wage Mythbusters" on its website, refuting the notion that high minimum wages can hurt businesses and the economy. Numerous activists and interest groups have passionately debated about a minimum wage hike, before, during, and after its enactment. These debates and counterpoints are not always backed by data-based evidence and often rely on anecdotal arguments.

The partisan nature of the debate and the ambivalence surrounding possible impacts of a higher minimum wage prompt my investigation. I focus on the entrepreneurship dimension, and bring new empirical insights to bear on the debate of minimum wage legislations.

My work centers on the survival rates of entrepreneurship, and I motivate two testable hypotheses. The first hypothesis evaluates whether minimum wage hikes hinder startup survival rates, whereas the second hypothesis evaluates whether minimum wage hikes jeopardize the conditional survival rates of young firms. I consider a panel regression framework in which the dependent variable is the survival rate of startups (or the conditional survival rate of young firms, respectively), and the independent variable is the state minimum wage, incorporating state and year fixed effects, as well as a control for state economic conditions.

One key finding is that a 1% increase in the minimum wage is associated with a 3.5% decline in the survival rates of startups, and this decline ranges between 1.8% and 5.2% across various restricted samples. Second, the negative effect of minimum wage hikes on the conditional survival rates is less severe among firms of age two years, and disappears among firms of ages three to five years. These bottom line conclusions hold under a number of robustness exercises, including a sampling strategy of putting states into randomized buckets, as well as the evidence from rolling and expanding schemes. I carefully address potential identification issues and endogeneity concerns, and an instrumental variable approach provides confirmatory supporting evidence.

Related literature. Even though business groups representing small-business owners are among the most vocal opponents of minimum wage hikes, there is no investigative study on how minimum wage impacts entrepreneurship. My work attempts to fill such a gap.

There is a corresponding paucity of research on how higher minimum wages influence business. Waltman, McBride, and Camhout (1998) look at the relationship between the *federal* minimum wage and the business failure rate from 1949 to 1983, and conclude that there is no relation. Additionally, Levin-Waldman (2000) examines survey data on 560 small-business owners with an inconclusive verdict on how minimum wage impacts businesses. Draca, Machin, and Van Reenen (2011) show that the introduction of a minimum wage reduced firm profitability in the UK, while Koellinger and Thurik (2012) establish a link between entrepreneurship and business cycles.

The vantage point of my data set that tabulates continuing and dead firms is of direct relevance and interest to the discourse about minimum wage policies. I exploit cross-sectional variation in state minimum wage legislation, as well as the variation in survival rates of startups and young firms. This allows me to draw economically relevant and data-grounded conclusions on how minimum wage hikes affect the livelihoods of entrepreneurs.

My focus on entrepreneurial outcomes transcends existing controversies about the effect of the minimum wage on unemployment and wage inequalities, and is worthy in its own right to the macroeconomy.

2. Gauging the impact of minimum wage on entrepreneurship

The missing piece addressed in this paper is whether increases in the minimum wage adversely impact entrepreneurship. This is a pivotal question, as entrepreneurship is a main driver of job creation, innovation, and new technologies in the economy. My interest centers on the test design and the isolation of the effect, exploiting information on state-level entrepreneurial activities and minimum wage policies.

2.1. Hypothesis development

Startups are one of the key objects of interest. Throughout, I define a startup as a newly created firm of *age one year*. These are firms in their infancy.[2]

A new firm usually begins small, as the owner tends to have some expertise but initially hires low-skilled workers to help with the business (e.g., Panda Express). These helpers, often part-time employees, frequently earn the minimum wage and earn limited fringe benefits. When there is a mandatory increase in minimum wage, the entrepreneur faces the prospect of higher labor costs, possibly with negative effects on the business.

There is another channel that may work in conjunction, namely, a spillover effect. Higher-

[2] Although technology startups attract a lot of attention, most startups are restaurants and other mundane service businesses.

skilled workers could demand higher pay in the face of a higher minimum wage. Therefore, minimum wage hikes could translate into higher payrolls for startups that hire both low- and higher-skilled workers.[3]

Additionally, startups are vulnerable and typically financially constrained, making them more sensitive to potential increases in labor costs. The advocacy against minimum wage hikes often rests on the argument that new firms are in a delicate position (e.g., Roth (2011)). Being at the cusp of "up or out," the commanded minimum wage hikes can hurt the bottom line of entrepreneurs and close down these businesses in their incipient stages. Surviving the first year as an entrepreneur is a landmark event, and I probe the following testable hypothesis:

Hypothesis 1 (Stifling hypothesis): *An increase in the minimum wage lowers the survival rates of startups.*

The learning curve for a new firm is usually steep in the first few years. As startups advance to their second, third, fourth, and fifth years, the entrepreneurs have learned to maneuver around their hurdles, presumably becoming more established and entrenched in their businesses. Even though minimum wage hikes erode their bottom lines, these entrepreneurs are better prepared to adapt and survive. To stay in business, these young firms can raise prices, cut workforce, and shorten the working hours of their employees. Some entrepreneurs take minimum wage hikes in stride and implement new technologies to reduce human labor. Additionally, some entrepreneurs scale back on their business offerings in the short run to minimize costs, hoping for better business prospects that offset the stipulated higher labor costs. Finally, some entrepreneurs have transitioned to a higher-skilled workforce and no longer have any minimum wage employees.

[3] Some perceived benefits of a higher wage are not applicable to startups. For example, a higher wage tends to increase the quality of new hires, reduce costs associated with on-the-job training, and lower worker turnover. In contrast, for startups, it is unlikely that they hire higher-skilled workers to fill in positions paying minimum wage. Startups care little about training workers or about a lower turnover rate, because the replacement costs are low.

When considering entrepreneurial activities beyond the startup stage, my emphasis is on conditional survival rates of young firms. Specifically, the year n survival rate measures the probability of age n firms to survive in year n, conditional on these firms having survived $n-1$ year.

I consider $n = 2, 3, 4, 5$, and ask: If there is an increase in the minimum wage, does it impact the survival of entrepreneurs, conditional on having survived until last year? The focus on conditional survival rates ties with my goals to study entrepreneurship, whereby if an entrepreneur survives its first year as a startup, it transitions toward viability. Aimed at bringing the issue of young firms to the forefront, I pose the following testable hypothesis:

Hypothesis 2 (Attenuation hypothesis): *An increase in the minimum wage has a negative effect on the conditional survival rates of young firms, which dissipates with age n.*

The two hypotheses bring together crucial aspects of entrepreneurship. The first-year survival rates of new firms assess the vulnerability of startups, whereas the survival rates of young firms show how much success entrepreneurs are generating and reflect their ability to weather economic headwinds. To my knowledge, this is the first study to quantify the impact of minimum wage on the survival rates of startups and on the conditional survival rates of young firms.

My design and focus on conditional survival rates allow me to offer evidence on the effects of minimum wage on distinct segments of entrepreneurship, namely, the startups that are vulnerable, versus young firms that may be less vulnerable. Together, these hypotheses speak to the core question of how minimum wage impacts the health of entrepreneurship. The debate on minimum wage has neglected these issues and would benefit from my perspectives. Possible concerns about identification and endogeneity are addressed in the context of my empirical specifications.

2.2. *Unique state-level data on entrepreneurship*

All featured metrics of entrepreneurial activities are constructed from the Business Dynamics Statistics (BDS) database. The BDS is generated from the Census Bureau's Longitudinal Business Database and records annual measures of business dynamics among private firms in the United States. The main source of the data is the Business Register, a database of U.S. business establishments and companies, maintained by the Census Bureau. Available from 1977 to 2014, the data set covers all industry groups, with age and size information on firms, and encompasses all 50 states and the District of Columbia.

BDS facilitates the annual count of firms of ages one, two, three, four, and five years, which is critical for assessing the impact of minimum wage hikes on entrepreneurship. Since the count of five-year-old firms was rendered feasible for the first time in 1982, I focus on the 33-year period from 1982 to 2014. A more detailed description of the data can be found at http://www.census.gov/ces/dataproducts/bds/index.html.

The BDS database allows me to differentiate among the possible dimensions of entrepreneurship. Using information on firm age, I can separately count the number of startups (aged one year) and young firms (aged two to five years) in each of the 50 states and the District of Columbia. This attribute of data availability facilitates a panel regression framework with state and year fixed effects, helping to isolate the link between minimum wage hikes and state-level entrepreneurship, while controlling for state-specific economic conditions. Additionally, the sample period covers several booms and recessions, which enables me to assess the validity of the hypotheses in diverse economic and credit conditions.[4]

[4] The BDS data has some advantages relative to other data sets. For example, the Longitudinal Business Database, which is the underlying micro data of the BDS, is confidential and only allows access to 12 states. Alternatively, the Business Employment Dynamics data provides survival rates of business establishments by state, but has been available since 1994. Finally, the Local Employment Dynamics data and the Quarterly Workforce Indicators do not provide counts of dead firms and have been available since 1992.

I define the year $t-1$ to year t startup survival rate, denoted by Startup Survival Rate$_{\mathbf{s},t}$, as the survival rate of age one firms in state $\mathbf{s}$:

$$\text{Startup Survival Rate}_{\mathbf{s},t} \equiv \frac{\text{Firms}^{[1]}_{\mathbf{s},t}}{\text{Firms}^{[1]}_{\mathbf{s},t} + \text{Dead Firms}^{[1]}_{\mathbf{s},t}}, \tag{1}$$

where Firms$^{[1]}_{\mathbf{s},t}$ is the number of age one firms, and Dead Firms$^{[1]}_{\mathbf{s},t}$ is the number of age one firms classified as firm deaths in state $\mathbf{s}$, both reported by BDS in year t.

Importantly, the BDS defines an age one firm in year t as a firm that reports positive employment in March of year $t-1$ for the first time in the database, and reports positive employment again in March of year t. An age one dead firm in year t is a (startup) firm exit that occurred sometime between the March of year $t-1$ and the March of year t. Therefore, Startup Survival Rate$_{\mathbf{s},t}$ measures the proportion of startups that remain in business from March of year $t-1$ to March of year t. The startup survival rates map to the *stifling hypothesis*.

Consider California, the state with the largest average number of startups, as an example. Reported by BDS in March 2014 are 41,354 age one firms and 9,359 dead age one firms. Accordingly, I compute Startup Survival Rate$_{\text{California},2014} = 41354/(41354+9359) = 81.5\%$.

I define the Young Firm Survival Rate$^{[n]}_{\mathbf{s},t}$ as the conditional survival rate of age two-, three-, four-, and five-year firms in state $\mathbf{s}$ over year $t-1$ to year t (i.e., March to March) as

$$\text{Young Firm Survival Rate}^{[n]}_{\mathbf{s},t} \equiv \frac{\text{Firms}^{[n]}_{\mathbf{s},t}}{\text{Firms}^{[n]}_{\mathbf{s},t} + \text{Dead Firms}^{[n]}_{\mathbf{s},t}}, \quad n = 2,3,4,5, \tag{2}$$

where Firms$^{[n]}_{\mathbf{s},t}$ is the number of age n firms, and Dead Firms$^{[n]}_{\mathbf{s},t}$ is the number of age n firms classified as firm deaths in state $\mathbf{s}$, reported by BDS in year t. Young Firm Survival Rate$^{[n]}_{\mathbf{s},t}$ is a conditional survival rate – conditional on having survived $n-1$ year – Young Fim Survival Rate$^{[n]}_{\mathbf{s},t}$

measures the fraction of young firms that continue to survive until year n and maps to the *attenuation hypothesis*.[5]

A potential caveat of computing the survival rates is that the BDS identifies a dead firm as a firm exit in which all the establishments associated with the firm (and the firm itself) cease all operations. Mergers, acquisitions, and reorganizations are not classified as firm exits, while such activities change the counts of firms (http://www.census.gov/ces/dataproducts/bds/definitions.html). My focus on startups and young firms helps to avoid potential inference problems associated with these activities among older firms. It is unlikely that a large number of new firms engage in such consolidations in the first five years of their inception.[6]

Three other observations are in order. First, self-employed individuals (i.e., sole proprietorships, partnerships, and independent contractors) do not constitute a private firm and are excluded. Second, the startup survival rate is distinct from the concept of startup rates. The latter is defined as the number of newly created firms over the total number of firms and differentiates my study in essential ways from Black and Strahan (2002). Finally, I consider the average effects of minimum wage hikes, given that BDS does not provide counts of live and dead firms in each industry at the state level.

Reported in Table 1 are the average survival rates of a startup alongside two-, three-, four-, and five-year conditional survival rates. The startup survival rates measure the fraction of startups that survived their first year and take an average value of 82.5%, which is somewhat higher than an average value of 75% reported among a group of 304 Danish entrepreneurs in Andersen and

[5]Consider again California as an illustration, where there were 25,654 five-year-old firms in 2014 and 2,559 dead five-year-old firms in the same year. Therefore, the year five survival rate Young Firm Survival $\text{Rate}^{[5]}_{\text{California},2014} = 25654/(25654+2559) = 90.9\%$.

[6]The unconditional survival rate of age n firm in year t can be computed as the number of age n firms in year t divided by the number of age zero year firms in year $t-n$. My analysis (based on the BDS data) indicates that the unconditional two-, three-, four-, and five-year survival rates are 65.8%, 57.8%, 51.6%, and 46.6%, respectively. This appears to contrast Roth (2011, page 15) and Colvin (2016), who suggest that most of the new firms tend to fail in the first few years.

Nielsen (2012, Table 5).

There is considerable variation in the startup survival rates across states and over years, ranging between 72.6% for Alaska in 1987 and 94.5% in Missouri in 1986.[7] Note that Nevada, Florida, and Mississippi have the lowest average startup survival rates, whereas D.C., Vermont, and North Dakota have the highest average startup survival rates. It is further seen that conditional on surviving the first year, 86.7% of the young firms remain in business after the second year. The average conditional survival rate increases to 88.5% (89.8%) in the third (fourth) year. If a firm has survived the first four years, as much as 90.8% of them can clock their fifth-year anniversary.

2.3. Evidence in favor of the stifling hypothesis

It is a standard practice in economics and finance to employ panel regression methodology to capture the effects of state policy changes. Some examples include Black and Strahan (2002) in their study of bank deregulation, Dick and Lehnert (2010) in their study on credit supply and personal bankruptcy rates, and Agrawal and Matsa (2013) in their study of unemployment insurance. Panel regression approach with fixed effects is also a favored strategy when investigating how minimum wage impacts unemployment (see the survey by Brown (1999)). While Dube, Lester, and Reich (2010) and Allegretto, Dube, and Reich (2011) argue that this approach can produce spurious negative effects of minimum wage on unemployment, Neumark, Salas, and Wascher (2014) and Neumark, Salas, and Wascher (2016) defend the practice.

[7] I purged eight state-year observations due to suspicious counts of firms, resulting in a startup survival rate higher than 99%. These are Virginia in 1985, Indiana in 1984, Wisconsin in 1987, D.C. in 1985, South Carolina in 1984, North Carolina in 1984, Maryland in 1985, and West Virginia in 1985. I trace these anomalous observations to low counts of dead firms.

2.3.1. *Motivating the empirical specification with state and year fixed effects*

In line with the extant research, I investigate the impact of minimum wage on the startup survival rates through a panel regression specification of the type:

$$\begin{aligned} \log(\text{Startup Survival Rate}_{\mathbf{s},t}) &= \alpha + \beta \log(\text{Minimum Wage}_{\mathbf{s},t-1}) + \gamma \log(\text{GPI}_{\mathbf{s},t}) \\ &\quad + \eta_{\mathbf{s}} + \tau_t + \varepsilon_{\mathbf{s},t}, \quad \mathbf{s} = 1, \ldots, 51, \;\; t = 2, \ldots, 33, \end{aligned} \tag{3}$$

where Startup Survival Rate$_{\mathbf{s},t}$ corresponds to the startup survival rates (as defined in equation (1)) of state $\mathbf{s}$ in year t (e.g., March 1999 to March 2000), and Minimum Wage$_{\mathbf{s},t-1}$ is the effective (nominal) minimum wage in state $\mathbf{s}$ in year $t-1$, observed in March (e.g., March 1999). The minimum wage data is described in Appendix A. Throughout, I rely on *robust* standard errors to draw statistical inferences (e.g., Dick and Lehnert (2010, pages 666 and 667) and Wooldridge (2010)).

The (log) gross personal income growth, denoted by GPI$_{\mathbf{s},t}$, is employed as a control, where GPI$_{\mathbf{s},t}$ is the ratio of the nominal personal income of state $\mathbf{s}$ in the first quarter of year t to its value in the first quarter of year $t-1$. The data source is described in Appendix A.

In equation (3), $\eta_{\mathbf{s}}$ is the state fixed effect and τ_t is the year fixed effect. I motivate the presence of state and year fixed effects from several perspectives:

- I implement the Hausman test and find that it rejects a random-effects model and favors a fixed-effects model (Roberts and Whited (2013)). The p-value is 0.000.
- Next, the F-test rejects the null of no fixed effects with a p-value of 0.000.

In addition, given the problems associated with not knowing the functional form, a state-specific trend on the startup survival rates is not imposed. I am guided by Neumark, Salas, and

Wascher (2016, page 1), who argue that picking an arbitrary form of a state trend can lead to spurious conclusions. The continuous county approach, advocated in Dube, Lester, and Reich (2010), seems appealing, but I do not use or have access to county-level entrepreneurship data.

The panel data analysis with state and year fixed effects can be expected to yield reliable inferences on the impact of minimum wage on entrepreneurship, but what about possible endogeneity concerns? Endogeneity is less of a concern in my test setting, as it is not likely that the viability of entrepreneurship can *simultaneously* impact the state legislations on minimum wage. I am agnostic that some unobserved variables can drive both the minimum wage laws and the survival rates (beyond what is captured by the personal income growth and the state and year fixed effects). To alleviate remaining endogeneity concerns, I also consider an empirical specification with lagged minimum wage as an instrument, results from which will be presented shortly.

2.3.2. Results from full sample, sampling strategies, and rolling and expanding schemes

Table 2 reports the results from my specification (3). The full sample contains 1,624 state-year observations, and lends support to the *stifling hypothesis*.

Specifically, the regression coefficient β for log(Minimum Wage) is negative in Panel A of Table 2 and statistically significant with p-value below 0.01. Additionally, the pooled correlation between the (log) startup survival rate and the (log) minimum wage is -0.2. The β estimate of -0.035 has an elasticity interpretation: a 1% increase in the minimum wage lowers the startup survival rates by 3.5%.

In my sample, minimum wage promulgations account for 30% of the 1,624 state-year observations. These changes are thus sufficiently frequent and salient, and can enable a sharper identification of the effect on the startup survival rates.

Consistent with intuition, the personal income growth has a significantly positive impact on the startup survival rates. Such a positive impact agrees with a notion that startup survival rates are associated with better economic conditions in the state. The goodness of fit is reasonable with an overall R^2 of 74.0%.

The reported coefficient reveals an economically important effect of minimum wage on startup survival rates. A one-standard deviation increase in the (log) minimum wage of 0.282 translates into a 1% decline in the (log) startup survival rate. This is nontrivial, as it represents one-third of the standard deviation in the (log) startup survival rate (0.03). Analogously, a one-standard deviation increase in the (log) personal income growth rate (0.030) is associated with a 1% increase in the (log) startup survival rates. In sum, minimum wage hikes significantly reduce the probability of startups to survive in year one, and the impact is comparable to that of personal income growth.[8]

The minimum wage is also individually statistically significant in the absence of personal income growth as a control (i.e., $\gamma \equiv 0$). In the restricted panel regression, I obtain a β estimate of -0.049 (with a p-value of 0.000) and an R^2 of 70.2%.

I am guided by a concern that after controlling for state economic conditions, and the state and year fixed effects, the residuals may still be correlated in the same state across the years, and/or correlated in the same year across the states. For this reason, I follow Petersen (2009) and Thompson (2011) and address concerns that the standard errors could be downward biased. With this in mind, I estimate the standard errors with clustering at the state level, and such clustering increases the p-value on the β estimate to 0.02. Next, I estimate the standard errors with clustering at the year level, and the p-value of the β estimate stays below 0.01. Thus, my findings are robust

[8] I feature results based on the nominal minimum wage because much of the debate on minimum wage is exclusively about nominal increase (see the surveys by Brown (1999) and Neumark, Salas, and Wascher (2016)). When I construct real minimum wage as the nominal minimum wage divided by the consumer price index, the panel regression results are equally strong and statistically significant. These results are omitted to save space.

under clustered standard errors.

Two exercises can help to further corroborate the impact of minimum wage on startup survival rates. First, I follow a sampling strategy and randomly divide states into two groups ordered by (i) name of the state, and (ii) name of the state capital. The results reported in Panel B of Table 2 indicate that the response of startup survival rates to minimum wage is both qualitatively and quantitatively robust. The β estimates range between -0.029 and -0.042 and are statistically significant, affirming that the effect is preserved in my randomization procedure.

Are startups more susceptible to minimum wage hikes in small-sized states versus large-sized states, where size is measured by the average state GDP? Panel C of Table 2 indicates that the negative impact of minimum wage hikes is magnified in smaller states as opposed to larger states. For example, the β estimate is -0.045 (-0.021) in low- (high-) sized states.

There are other ways to divide the sample of states. For example, I divide the states according to the average union participation rates from the Bureau of Labor Statistics (see also Allegretto, Dube, Reich, and Zipperer (2013, Table 1)). The union participation rate is the percentage of employed workers who are union members. The β estimates remain negative and statistically significant for both low and high union participation rate states (see Panel D of Table 2).

There are many proposals underway, prominently in state of Washington, where the minimum wage is about to be elevated to \$15. Moreover, important for policy in the current politically charged economic environment with anemic growth rates, one may be interested in assessing the impact of minimum wage hikes on entrepreneurship over the past two decades. For this purpose, I implement both a rolling scheme and an expanding scheme. In the rolling scheme, I move backward in two five-year increments over two decades (i.e., 1995 to 2014 and 1991 to 2010), while under the expanding scheme, I keep on adding five years of additional data.

Over the prior twenty-year sample of 1995 to 2014 (Panel A of Table 3), the estimate of β is -0.033 and is statistically significant. The takeaway from the results of rolling and expanding schemes in Table 3 is that the β estimates are negative and fairly stable between -0.028 and -0.052, and strengthen my findings over diverse economic conditions.

Overall, the exercises in Tables 2 and 3 suggest that minimum wage hikes have a negative effect on the survival rate of startups. These findings support the stifling hypothesis.

I also consider an exercise in which the dependent variable is the *level* of the startup survival rates. As seen in Table Appendix-I, the coefficients on the log of minimum wage are all negative and statistically significant. The coefficient of -0.029 indicates that a one-standard deviation increase in the log of minimum wage (0.282) leads to 0.8% decline in the startup survival rates. Such decline is economically important, as it is more than one-third of the standard deviation in the level of the startup survival rates (0.025).

Finally, a widely adopted approach to account for endogeneity is the use of instruments (e.g., Roberts and Whited (2013)). I consider the lagged minimum wage as an instrument and assess its impact on entrepreneurship within the context of the empirical specification (3) with state and year fixed effects. The panel estimation results, reported in Table Appendix-II, indicate that the startup survival rate is negatively related to lagged minimum wage. For example, the estimated coefficient is -0.036 in the full sample and is statistically significant.[9]

[9] Is the negative impact of minimum wage hikes on startup survival rates robust if I include lags of the control variable, or if I consider additional controls in specification (3)? First, I include up to six lags of the personal income growth (as in Black and Strahan (2002, Table IV)) and obtain similar overall picture. Second, I consider statewide unemployment rates as an additional control and obtain similar findings. These results are available.

2.4. *Evidence in favor of the attenuation hypothesis*

Next, I consider an empirical framework that relates the conditional survival rate of young firms of age n to minimum wage, for $n = 2,3,4,5$,

$$\begin{aligned}\log\left(\text{Young Firm Survival Rate}_{\mathbf{s},t}^{[n]}\right) &= \alpha^{[n]} + \beta^{[n]} \log(\text{Minimum Wage}_{\mathbf{s},t-1}) + \gamma^{[n]} \log(\text{GPI}_{\mathbf{s},t}) \\ &\quad + \eta_{\mathbf{s}}^{[n]} + \tau_t^{[n]} + \varepsilon_{\mathbf{s},t}^{[n]}, \quad \mathbf{s} = 1,\ldots,51, \;\; t = 2,\ldots,33, \qquad (4)\end{aligned}$$

where Young Firm Survival Rate$_{\mathbf{s},t}^{[n]}$ is the survival rate of firms of ages two, three, four, and five years in state $\mathbf{s}$ over year $t-1$ to year t.

Estimates of $\beta^{[n]}$ that are negative and diminishing with n constitute support for the attenuation hypothesis. In addition, I am interested in testing the null hypothesis: (i) $\beta^{[1]} = \beta^{[2]}$, (ii) $\beta^{[2]} = \beta^{[3]}$, (iii) $\beta^{[3]} = \beta^{[4]}$, and (iv) $\beta^{[4]} = \beta^{[5]}$, which I implement in a seemingly unrelated regression (SUR) system (e.g., Wooldridge (2010)).

In contrast to the significantly negative and sizable impact of minimum wage hikes on startup survival rates, Panel A of Table 4 points to a smaller and weaker impact on the year two survival rates. This conclusion can be gleaned from different angles. First, the full sample $\beta^{[2]}$ estimate is -0.018, implying that a one-standard deviation change in the (log) minimum wage reduces the (log) year two survival rate by 0.005, about one-quarter of the standard deviation in the (log) year two survival rates (0.02). Compared with an R^2 of 74.0% in Table 2, a lower R^2 of 65.9% is obtained.

The results from Tables 4 and 5 indicate that the $\beta^{[2]}$ estimates, while negative, are typically reduced by half compared to their $\beta^{[1]}$ counterparts, and sometimes not statistically significant. For example, in Panels C and D of Table 4, which divide the states by low versus high size or low versus high union rates, three out of four $\beta^{[2]}$ estimates exhibit p-values above 0.159. At the same time, the evidence from rolling and expanding schemes in Table 5 indicates that five out of six $\beta^{[2]}$ estimates are statistically significant. Overall, my empirical results imply that the negative effect of minimum wage on the year two conditional survival rates is milder (in comparison to the startup survival rates) and the statistical significance varies over the considered samples.

A different picture emerges when considering the survival rates of young firms aged three, four, and five years. Specifically, the results in Table 4 show that $\beta^{[3]}$ further drops down to -0.006 over the full sample and is statistically insignificant. Furthermore, the p-values on the $\beta^{[3]}$ estimates in Panels A to D of Table 4 are all above 0.21. I also find that $\beta^{[4]}$ and $\beta^{[5]}$ are generally insignificant over the full sample, in the restricted regressions that differentiate by size and union rate (see Table 4), and in rolling and expanding schemes (see Table 5). In contrast, Tables 4 and 5 show that the p-values on the personal income growth ($\gamma^{[n]}$) are always 0.000.

Finally, I test the null hypothesis $\beta^{[n-1]} = \beta^{[n]}$ for n = 2, 3, 4, and 5 in a SUR estimation framework. The $\chi^2(1)$ statistics, and the associated p-values, are tabulated below:

Null hypothesis	$\beta^{[1]} = \beta^{[2]}$	$\beta^{[2]} = \beta^{[3]}$	$\beta^{[3]} = \beta^{[4]}$	$\beta^{[4]} = \beta^{[5]}$
$\chi^2(1)$ $\{p$-val.$\}$	6.25 {0.01}	4.77 {0.03}	0.03 {0.86}	0.12 {0.73}

My results suggest that $\beta^{[1]}$ is statistically more negative than $\beta^{[2]}$, while $\beta^{[2]}$ is statistically more negative than $\beta^{[3]}$. In contrast, $\beta^{[3]}$, $\beta^{[4]}$, and $\beta^{[5]}$ are statistically indistinguishable from each other. This exercise provides further evidence on the attenuation hypothesis.

Taken all together, my estimations show that the effect of minimum wage on the conditional survival rates of young firms dissipates in n, and is statistically indistinguishable from zero among firms ages three, four, and five years. These results are consistent with the attenuation hypothesis and support the idea that young firms are able to absorb minimum wage hikes as they become more established and viable.

How should one assess the economic effects of minimum wage hikes across the universe of private firms? Below, I tabulate the distribution of startups and young firms in the BDS sample:

Age	1	2	3	4	5
Proportion of firms (%)	8.5	7.2	6.4	5.7	5.2

To compute these proportions, I follow two steps. First, I compute the number of firms from ages one to five years, and divide them respectively by the number of all viable firms (up to ages 26 years and older, including the category of age unknown) for each state and in each year. Next, I average these proportions across all the 33 years in each state, and then compute the overall average across all states.

This exercise shows that minimum wage hikes adversely impact a sizable portion (15.7%) of private firms, and this effect is both statistically and economically relevant. At the same time, 17.3% of the firms – aged three to five years – appear able to absorb minimum wage increases, as these increases do not materially influence their conditional survival rates. Specifically, the minimum wage increases become less harmful when a young firm advances into the second year, as the β estimates get progressively smaller in magnitude and weaker in statistical terms.

As a young firm continues to survive and develop, minimum wage hikes become irrelevant. The rationale is that sustained survival leads to a healthier firm that is resilient to adverse shocks to minimum wage. This is consistent with some arguments that wage laws aimed at lowering income inequalities can generate social benefits without unduly burdening businesses.

2.5. *Positioning my study in the long-standing debate about minimum wage*

The literature has traditionally focused on how minimum wage impacts unemployment and income distribution, but its impact on entrepreneurship remains rather unexplored.

Early evidence relies on time-series data and seems to suggest that minimum wage increases reduce employment among teenagers. Since then, studies have used cross-sectional data to refine the evidence, uncovering smaller effects of minimum wage (e.g., Card (1992a, 1992b), Katz and Krueger (1992), Card and Krueger (1994), and Machin and Manning (1994)). Brown (1999) provides a synthesis of the empirical findings and controversies.[10]

There is broader agreement on a negative relationship between minimum wage and wage inequality, that is, lower minimum wage is associated with greater income inequality. Studies have shown that the real value of federal minimum wage has declined by 30 log points between 1979 and 1988, which contributes to the rising wage inequality (Katz and Murphy (1992), Katz and Autor (1999), Card and DiNardo (2002), Autor, Katz, and Kearney (2008), Goldin and Katz (2009), Lemieux (2008), Acemoglu and Autor (2011), and Autor, Manning, and Smith (2016)). However, David, Manning, and Smith (2016) show that the impact of minimum wage on wage inequality is smaller than that established in many earlier studies (e.g., DiNardo, Fortin, and Lemieux (1996) and Lee (1999)).

Do increases in minimum wage reshape entrepreneurship by affecting their survival rates? An answer is important, as there is a broader consensus among academics, practitioners, and policymakers that startups and young firms are catalysts of job creation and innovation.

[10] There are some disagreements about ways to measure the employment effects of minimum wage and what minimum wage increases do to employment. The contentious nature of the findings is the focus of Dube, Lester, and Reich (2010), Allegretto, Dube, and Reich (2011), Neumark and Wascher (2007), Allegretto, Dube, Reich, and Zipperer (2013), and Neumark, Salas, and Wascher (2014). The work of Neumark, Salas, and Wascher (2016) reviews evidence on the impact of minimum wage on unemployment.

Casting additional light, my investigation is pertinent, given that new and young firms tend to have a workforce with higher proportion of minimum-wage workers. They often tend to operate on thin or even negative profit margins, leaving them exposed to mandated increases in labor costs in their incipient years. Even for startups that pay workers above the minimum wage, the spillover effects of a higher minimum wage could still lead to higher labor costs as higher-skilled workers may demand a relatively higher pay.

My work brings some resolution on how higher payrolls affect the survival rates of startups and young firms through a newly available data set, and my approach is grounded in established econometrics. Tables 2 to 5 are particularly telling in that I never obtain *a positive and statistically significant* impact of minimum wage increases on the survival rates of entrepreneurship.

3. Conclusions

Using a novel data set on entrepreneurship, the results of this paper suggest that the startup survival rates are adversely affected by minimum wage hikes. In particular, my panel regression approach shows that a 1% increase in the minimum wage tends to decrease the average startup survival rates by 3.5%. I further observe that the negative effect of minimum wage hikes are pronounced in states with lower average state GDP and in states with lower average union rates. Minimum wage increases have a negative connotation in that they hinder entrepreneurship by making startups more vulnerable. Startups constitute an average of 8.5% of the universe of private firms.

The impact of minimum wage increases on the conditional survival rates of firms of age two years is weaker but statistically significant in the full sample and in the majority of the rolling and expanding samples. Age two firms constitute an average of 7.2% of all private firms.

In contrast, firms of ages three, four, and five years constitute an average of 17.3% of all private firms, and my results are intriguing for these young firms: the impact of minimum wage increases on their conditional survival rates is essentially gone and is generally statistically insignificant. This is a silver lining in the narrative on minimum wage and income inequality. That is, conditional on an entrepreneur surviving $n-1$ year, the survival in year n, for $n = 3,4,5$, is not overly impacted by minimum wage increases, and this effect is further attenuated as the entrepreneur gets on his feet and internalizes minimum wage hikes. The empirical evidence points to the resilience of entrepreneurs as they adjust to changes in their business environment.

Legislative bodies should be aware of the possible negative externalities associated with the effects of minimum wage increases on startups. This entails remedial actions to offset any negative effects of minimum wage hikes on entrepreneurship. Entrepreneurship is an important fabric of job creation and innovation and should be fostered by lawmakers. This can be done without forsaking goals of social equality, and while championing legislations that dignify efforts of the minimum wage earners. For example, some leeway could be granted to startups when implementing new minimum wage policies.

A. Appendix A: Data on state minimum wage, personal income, and unemployment rates

I describe the data on state minimum wage, personal income, and unemployment rates.

Data on state minimum wage: The minimum wage records for each state are compiled from various sources. First, the monthly data is from Ian Salas, available at https://sites.google.com/site/jmisalas/. This data covers the minimum wage at state-month level from 1983 to 2013, with 18,972 state-month observations.

Next, I augment this data with the year 1982. The online appendix of Aaronson, Agarwal, and French (2012, Table A2) indicates that there is no minimum wage change in 1982 and 1983. Hence, the state minimum wages in 1982 are kept at the same level as those in 1983. Finally, the state minimum wages in 2014 is from the U.S. Department of Labor, available at https://www.dol.gov/whd/state/stateminwagehis.htm.

In certain years and certain states, there exist two minimum wage rates, which represent a multiple-track minimum-wage system. The lower rate is applicable to newly covered workers, and their rates were gradually increased to the higher rate. In this case, I take the midpoint of the range to be the minimum wage. Moreover, certain states have applied a different minimum wage for minors and women versus others. When I observe such a bifurcated minimum wage system, I take the midpoint of the range. I also dealt with cases in which the smallest firms qualify for a lower minimum wage rate. A case in point is Minnesota, in which I take the average of the two wage rates.

Data on state personal income: I use state personal income growth (source: Bureau of Economic Analysis (BEA)) as a control for state economic conditions. The state personal income growth rate and the state GDP growth (source: BEA) have a correlation of 0.67 over the available sample period of 1997 to 2014.

Data on state unemployment rates: I adopt the state unemployment rates as an additional control for state economic condition. This data is from the Bureau of Labor Statistics.

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Table 1

Survival rates of private firms in the 50 U.S. states and the District of Columbia

All computations are based on Business Dynamics Statistics (BDS) database, which facilitates the annual count of firms ages one, two, three, four, and five years. The year t startup survival rate is defined as $\text{Startup Survival Rate}_{\mathbf{s},t} \equiv \frac{\text{Firms}^{[1]}_{\mathbf{s},t}}{\text{Firms}^{[1]}_{\mathbf{s},t}+\text{Dead Firms}^{[1]}_{\mathbf{s},t}}$, where $\text{Firms}^{[1]}_{\mathbf{s},t}$ is the number of age one firms, and $\text{Dead Firms}^{[1]}_{\mathbf{s},t}$ is the number of age one firms classified as firm deaths, in state **s**. Isomorphically, I define $\text{Young Firm Survival Rate}^{[n]}_{\mathbf{s},t} \equiv \frac{\text{Firms}^{[n]}_{\mathbf{s},t}}{\text{Firms}^{[n]}_{\mathbf{s},t}+\text{Dead Firms}^{[n]}_{\mathbf{s},t}}$, for $n = 2,3,4,5$. Reported are the averages over 1982 to 2014.

State	Startup survival rates (%)	Young firm survival rates (%)			
		Year Two	Year Three	Year Four	Year Five
Across 50 states plus DC	82.5	86.7	88.5	89.8	90.8
Alabama	80.7	85.5	87.7	89.3	90.5
Alaska	81.3	86.7	88.4	89.6	90.9
Arizona	80.6	85.1	87.1	88.7	89.7
Arkansas	80.5	85.5	87.6	89.4	90.3
California	82.0	86.1	87.9	89.2	90.2
Colorado	81.2	85.7	87.7	89.3	90.2
Connecticut	84.2	87.4	89.2	90.1	91.1
Delaware	84.0	87.6	89.3	89.9	91.0
D.C.	85.2	88.7	89.9	91.3	91.5
Florida	80.0	84.5	86.7	88.3	89.5
Georgia	81.2	85.7	87.8	89.2	90.3
Hawaii	83.0	86.9	88.6	89.9	90.8
Idaho	82.3	86.6	88.4	89.8	90.8
Illinois	84.1	87.9	89.4	90.6	91.3
Indiana	82.7	86.8	88.7	90.1	90.9
Iowa	83.8	87.7	89.4	90.4	91.3
Kansas	82.0	86.4	88.3	89.6	90.6
Kentucky	82.2	86.2	88.0	89.5	90.4
Louisiana	81.6	86.1	88.1	89.7	90.6
Maine	83.8	87.7	89.2	90.4	91.4
Maryland	83.3	87.6	89.2	90.4	91.3
Massachusetts	84.3	87.8	89.3	90.3	91.1
Michigan	83.9	87.5	89.1	90.1	90.9
Minnesota	84.6	88.1	89.6	90.9	91.7
Mississippi	80.2	85.3	87.7	89.1	90.3
Missouri	81.0	85.5	87.7	89.3	90.4
Montana	82.7	87.3	89.2	90.3	91.1
Nebraska	84.8	88.0	89.7	90.6	91.6
Nevada	79.1	84.2	86.8	88.4	89.5
New Hampshire	83.2	86.9	88.6	89.9	90.7
New Jersey	83.5	87.3	88.9	90.0	90.8
New Mexico	81.2	86.0	87.9	89.5	90.4
New York	83.4	86.7	88.3	89.4	90.4
North Carolina	82.2	86.5	88.6	89.8	90.8
North Dakota	84.8	87.8	89.6	90.8	91.7
Ohio	83.5	87.3	89.1	90.4	91.1
Oklahoma	80.5	85.2	87.7	89.1	90.1
Oregon	81.9	86.3	88.3	89.7	90.5
Pennsylvania	84.7	88.3	89.8	91.0	91.8
Rhode Island	83.0	87.2	88.8	90.4	91.0
South Carolina	81.7	85.9	88.0	89.5	90.6
South Dakota	83.8	87.7	89.7	90.9	91.8
Tennessee	80.2	85.1	87.5	89.3	90.3
Texas	80.9	85.1	87.3	88.9	89.9
Utah	80.6	85.4	87.6	89.1	90.2
Vermont	84.9	88.0	89.4	90.8	91.2
Virginia	82.4	86.9	88.7	90.1	91.1
Washington	81.5	86.3	88.2	89.6	90.5
West Virginia	81.7	86.2	88.5	89.7	90.6
Wisconsin	84.3	88.1	89.7	90.9	91.7
Wyoming	82.9	86.8	88.8	89.8	90.7

Table 2
Minimum wage hikes negatively impact startup survival rates

This table reports the results from the panel regression specification:

$$\log(\text{Startup Survival Rate}_{\mathbf{s},t}) = \alpha + \beta \log(\text{Minimum Wage}_{\mathbf{s},t-1}) + \gamma \log(\text{GPI}_{\mathbf{s},t}) + \eta_{\mathbf{s}} + \tau_t + \varepsilon_{\mathbf{s},t}, \quad \mathbf{s} = 1,\ldots,51, \; t = 2,\ldots,33.$$

Startup Survival Rate$_{\mathbf{s},t}$ is the startup survival rate (as defined in equation (1)) of state $\mathbf{s}$ in year t (e.g., March 1999 to March 2000), and Minimum Wage$_{\mathbf{s},t-1}$ is the effective (nominal) minimum wage in state $\mathbf{s}$ in year $t-1$, observed in March (e.g, March 1999), and GPI$_{\mathbf{s},t}$ is the gross personal income growth. This specification allows for state and year fixed effects. Shown are the coefficient estimates, the robust standard errors (denoted as s.e., shown in parentheses), and the associated p-values (in curly brackets). Panel A reports the full sample results from 1983 to 2014. Panel B considers sampling schemes in which I randomly divide my sample of states (i.e., the 50 states and the District of Columbia) into two groups by (i) name of the state and (ii) name of the state capital. Panel C (respectively, Panel D) considers a restricted sample in which I divide the sample of states into low and high average state GDP (respectively, low and high average union rates). The reported R^2 represents the overall R^2, and Nobs is the number of observations.

	Panel A: Full sample	Panel B: Randomization				Panel C: Size		Panel D: Union rates	
	1983-2014	State initials		Capital initials		Low	High	Low	High
		I	II	I	II				
β	-0.035	-0.037	-0.029	-0.042	-0.030	-0.045	-0.021	-0.037	-0.018
s.e.	(0.008)	(0.012)	(0.011)	(0.014)	(0.010)	(0.012)	(0.011)	(0.017)	(0.010)
p-val.	{0.000}	{0.001}	{0.007}	{0.002}	{0.002}	{0.000}	{0.063}	{0.033}	{0.061}
γ	0.304	0.360	0.265	0.274	0.360	0.260	0.357	0.249	0.363
s.e.	(0.031)	(0.046)	(0.038)	(0.037)	(0.049)	(0.040)	(0.037)	(0.040)	(0.050)
p-val.	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
α	-0.167	-0.164	-0.151	-0.127	-0.177	-0.144	-0.154	-0.133	-0.203
s.e.	(0.017)	(0.023)	(0.022)	(0.028)	(0.020)	(0.025)	(0.023)	(0.035)	(0.020)
p-val.	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
R^2 (%)	74.0	73.2	76.0	72.5	75.7	72.3	77.8	73.2	74.4
Nobs	1624	829	795	827	797	829	795	827	797
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 3
Minimum wage hikes and startup survival rates under rolling and expanding schemes

Reported are the results over rolling and expanding schemes for the panel regression specification:

$$\log\left(\text{Startup Survival Rate}_{\mathbf{s},t}\right) = \alpha + \beta \log(\text{Minimum Wage}_{\mathbf{s},t-1}) + \gamma \log(\text{GPI}_{\mathbf{s},t}) + \eta_{\mathbf{s}} + \tau_t + \varepsilon_{\mathbf{s},t}, \quad \mathbf{s} = 1,\ldots,51, \ t = 2,\ldots,33.$$

Startup Survival $\text{Rate}_{\mathbf{s},t}$ is the startup survival rate (as defined in equation (1)) of state **s** in year t (e.g., March 1999 to March 2000), and Minimum $\text{Wage}_{\mathbf{s},t-1}$ is the effective (nominal) minimum wage in state **s** in year $t-1$, observed in March (e.g., March 1999), and $\text{GPI}_{\mathbf{s},t}$ is the gross personal income growth. This specification allows for state and year fixed effects. Shown are the coefficient estimates and the associated p-values (based on robust standard errors, in curly brackets). The reported R^2 represents the overall R^2.

	Panel A: Rolling scheme		Panel B: Expanding scheme			
	1995-2014	1991-2010	1983-2010	1983-2006	1983-2002	1983-1998
β	-0.033	-0.032	-0.038	-0.030	-0.028	-0.052
p-val.	{0.000}	{0.000}	{0.000}	{0.014}	{0.030}	{0.002}
γ	0.201	0.248	0.326	0.318	0.316	0.320
p-val.	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
α	-0.167	-0.172	-0.161	-0.204	-0.167	-0.167
p-val.	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
R^2 (%)	74.8	80.0	76.1	74.9	77.2	76.8
Nobs	1020	1020	1420	1216	1012	808
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 4
Minimum wage hikes and the survival rates of young firms

All reported results are based on the panel regression specification, for $n = 2,3,4,5$:

$$\log(\text{Young Firm Survival Rate}_{\mathbf{s},t}^{[n]}) = \alpha^{[n]} + \beta^{[n]} \log(\text{Minimum Wage}_{\mathbf{s},t-1}) + \gamma^{[n]} \log(\text{GPI}_{\mathbf{s},t}) + \eta_{\mathbf{s}}^{[n]} + \tau_t^{[n]} + \varepsilon_{\mathbf{s},t}^{[n]}, \quad \mathbf{s} = 1,\ldots,51, \ \ t = 2,\ldots,33,$$

where Young Firm Survival Rate$_{\mathbf{s},t}^{[n]}$ is the survival rate of firms ages two, three, four, and five years in state $\mathbf{s}$ over year $t-1$ to year t, and allows for state and year fixed effects. Shown are the coefficient estimates and the associated p-values (based on robust standard errors, in curly brackets). Panel A reports the full sample results over 1983 to 2014. Panel B considers sampling schemes in which I randomly divide my sample of states into two groups by (i) name of the state and (ii) name of the state capital. Panel C (Panel D) considers a restricted sample in which I divide the sample of states into low and high average state GDP (low and high average union rates). The reported R^2 is the overall R^2.

	Panel A: Full sample	Panel B: Randomization				Panel C: Size		Panel D: Union rates	
	1983-2014	State initials		Capital initials		Low	High	Low	High
		I	II	I	II				
				I: Year two survival rates					
$\beta^{[2]}$	-0.018	-0.027	-0.006	-0.023	-0.015	-0.029	-0.009	-0.017	-0.010
p-val.	{0.002}	{0.001}	{0.495}	{0.012}	{0.048}	{0.004}	{0.223}	{0.293}	{0.159}
$\gamma^{[2]}$	0.246	0.278	0.231	0.224	0.288	0.207	0.323	0.217	0.279
p-val.	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
$\alpha^{[2]}$	-0.122	-0.104	-0.132	-0.099	-0.127	-0.099	-0.113	-0.107	-0.141
p-val.	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
R^2 (%)	65.9	67.3	65.4	63.3	69.1	62.6	73.1	66.0	63.3
				II: Year three survival rates					
$\beta^{[3]}$	-0.006	-0.008	-0.003	-0.011	-0.001	-0.007	-0.001	-0.019	0.005
p-val.	{0.280}	{0.284}	{0.714}	{0.210}	{0.836}	{0.483}	{0.845}	{0.238}	{0.445}
$\gamma^{[3]}$	0.217	0.234	0.206	0.197	0.255	0.199	0.248	0.185	0.254
p-val.	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
$\alpha^{[3]}$	-0.119	-0.116	-0.113	-0.096	-0.130	-0.115	-0.108	-0.080	-0.141
p-val.	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.001}	{0.000}
R^2 (%)	59.5	61.3	59.0	56.2	64.5	54.5	69.0	59.9	58.3
				III: Year four survival rates					
$\beta^{[4]}$	-0.007	-0.011	-0.001	-0.014	-0.001	-0.011	-0.002	-0.017	0.003
p-val.	{0.163}	{0.099}	{0.887}	{0.083}	{0.882}	{0.199}	{0.773}	{0.244}	{0.581}
$\gamma^{[4]}$	0.189	0.219	0.172	0.182	0.203	0.168	0.227	0.172	0.215
p-val.	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
$\alpha^{[4]}$	-0.099	-0.092	-0.105	-0.079	-0.112	-0.089	-0.094	-0.072	-0.120
p-val.	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.002}	{0.000}
R^2 (%)	54.3	57.0	52.7	50.0	60.8	48.1	66.3	53.2	55.7
				IV: Year five survival rates					
$\beta^{[5]}$	-0.009	-0.014	0.000	-0.012	-0.006	-0.013	-0.001	-0.025	-0.002
p-val.	{0.095}	{0.056}	{0.961}	{0.170}	{0.293}	{0.153}	{0.864}	{0.066}	{0.781}
$\gamma^{[5]}$	0.174	0.210	0.152	0.176	0.176	0.158	0.196	0.162	0.189
p-val.	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
$\alpha^{[5]}$	-0.081	-0.072	-0.096	-0.069	-0.089	-0.069	-0.087	-0.046	-0.097
p-val.	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.027}	{0.000}
R^2 (%)	50.1	49.7	52.8	46.3	55.8	44.1	62.0	52.6	47.7

Table 5

Minimum wage hikes and survival rates of young firms under rolling and expanding schemes

Reported are the results over rolling and expanding schemes for the panel regression specification, for $n = 2,3,4,5$:

$$\log\left(\text{Young Firm Survival Rate}_{\mathbf{s},t}^{[n]}\right) = \alpha^{[n]} + \beta^{[n]} \log(\text{Minimum Wage}_{\mathbf{s},t-1}) + \gamma^{[n]} \log(\text{GPI}_{\mathbf{s},t}) + \eta_{\mathbf{s}}^{[n]} + \tau_t^{[n]} + \varepsilon_{\mathbf{s},t}^{[n]}, \quad \mathbf{s} = 1,\ldots,51, \ t = 2,\ldots,33,$$

where Young Firm Survival Rate$_{\mathbf{s},t}^{[n]}$ is the survival rate of firms ages two, three, four, and five years in state $\mathbf{s}$ over year $t-1$ to year t, and allows for state and year fixed effects. Shown are the coefficient estimates and the associated p-values (based on robust standard errors, in curly brackets). The reported R^2 represents the overall R^2.

	Panel A: Rolling scheme		Panel B: Expanding scheme			
	1995-2014	1991-2010	1983 - 2010	1983 - 2006	1983 - 2002	1983 - 1998
I: Year two survival rates						
$\beta^{[2]}$	-0.014	-0.008	-0.018	-0.018	-0.019	-0.028
p-val.	{0.023}	{0.156}	{0.002}	{0.004}	{0.021}	{0.012}
$\gamma^{[2]}$	0.182	0.213	0.246	0.259	0.250	0.247
p-val.	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
$\alpha^{[2]}$	-0.129	-0.151	-0.122	-0.132	-0.146	-0.108
p-val.	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
R^2 (%)	72.9	72.4	65.9	66.3	65.3	66.4
II: Year three survival rates						
$\beta^{[3]}$	-0.007	0.001	-0.006	-0.005	0.001	-0.003
p-val.	{0.256}	{0.826}	{0.280}	{0.397}	{0.869}	{0.782}
$\gamma^{[3]}$	0.118	0.159	0.217	0.235	0.238	0.250
p-val.	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
$\alpha^{[3]}$	-0.116	-0.142	-0.119	-0.129	-0.154	-0.123
p-val.	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
R^2 (%)	68.1	63.1	59.5	58.1	56.3	56.3
III: Year four survival rate						
$\beta^{[4]}$	-0.010	-0.008	-0.007	-0.007	-0.008	-0.020
p-val.	{0.055}	{0.145}	{0.163}	{0.157}	{0.201}	{0.031}
$\gamma^{[4]}$	0.097	0.120	0.189	0.199	0.199	0.211
p-val.	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
$\alpha^{[4]}$	-0.091	-0.105	-0.099	-0.106	-0.111	-0.076
p-val.	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
R^2 (%)	65.1	60.4	54.3	52.9	48.7	48.0
IV: Year five survival rate						
$\beta^{[5]}$	-0.015	-0.009	-0.009	-0.009	-0.007	-0.007
p-val.	{0.012}	{0.111}	{0.095}	{0.091}	{0.354}	{0.406}
$\gamma^{[5]}$	0.105	0.133	0.174	0.183	0.174	0.177
p-val.	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
$\alpha^{[5]}$	-0.067	-0.090	-0.081	-0.089	-0.100	-0.091
p-val.	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
R^2 (%)	58.0	55.3	50.1	49.0	44.6	45.0

Table Appendix-I

Relation between minimum wage hikes and the level of the startup survival rates

This table reports the results from the panel regression specification:

$$\begin{aligned}\text{Startup Survival Rate}_{\mathbf{s},t} &= \alpha + \beta \log(\text{Minimum Wage}_{\mathbf{s},t-1}) + \gamma \log(\text{GPI}_{\mathbf{s},t}) \\ &\quad + \eta_{\mathbf{s}} + \tau_t + \varepsilon_{\mathbf{s},t}, \quad \mathbf{s} = 1,\ldots,51, \;\; t = 2,\ldots,33.\end{aligned}$$

Startup Survival Rate$_{\mathbf{s},t}$ is the startup survival rate (as defined in equation (1)) of state **s** in year t (e.g., March 1999 to March 2000), and Minimum Wage$_{\mathbf{s},t-1}$ is the effective (nominal) minimum wage in state **s** in year $t-1$, observed in March (e.g., March 1999), and GPI$_{\mathbf{s},t}$ is the gross personal income growth. This specification allows for state and year fixed effects. Shown are the coefficient estimates, the robust standard errors (denoted as s.e., shown in parentheses), and the associated p-values (in curly brackets). Panel A reports the full sample results from 1983 to 2014. Panel B considers sampling schemes in which I randomly divide my sample of states (i.e., the 50 states and the District of Columbia) into two groups by (i) name of the state and (ii) name of the state capital. Panel C (respectively, Panel D) considers a restricted sample in which I divide the sample of states into low and high average state GDP (respectively, low and high average union rates). The reported R^2 represents the overall R^2, and Nobs is the number of observations.

	Panel A:	Panel B:				Panel C:		Panel D:	
	Full sample	Randomization				Size		Union rates	
	1983-2014	State initials		Capital initials		Low	High	Low	High
		I	II	I	II				
β	-0.029	-0.030	-0.024	-0.035	-0.024	-0.038	-0.017	-0.030	-0.015
s.e.	(0.007)	(0.009)	(0.009)	(0.011)	(0.008)	(0.010)	(0.009)	(0.014)	(0.008)
p-val.	{0.000}	{0.001}	{0.007}	{0.002}	{0.003}	{0.000}	{0.064}	{0.035}	{0.063}
γ	0.246	0.291	0.215	0.223	0.290	0.209	0.289	0.201	0.295
s.e.	(0.025)	(0.037)	(0.031)	(0.030)	(0.039)	(0.033)	(0.030)	(0.032)	(0.039)
p-val.	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
α	0.846	0.848	0.860	0.880	0.837	0.866	0.856	0.873	0.816
s.e.	(0.014)	(0.019)	(0.018)	(0.023)	(0.016)	(0.021)	(0.019)	(0.029)	(0.016)
p-val.	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
R^2(%)	74.1	73.4	76.0	72.6	75.7	72.4	77.9	73.2	74.6
Nobs	1624	829	795	827	797	829	795	827	797

Table Appendix-II
Relation between minimum wage hikes and the startup survival rates, when lagged minimum wage is adopted as an instrument

This table reports the results from the panel regression specification:

$$\log(\text{Startup Survival Rate}_{\mathbf{s},t}) = \alpha + \beta \log(\text{Minimum Wage}_{\mathbf{s},t-2}) + \gamma \log(\text{GPI}_{\mathbf{s},t}) + \eta_{\mathbf{s}} + \tau_t + \varepsilon_{\mathbf{s},t}, \quad \mathbf{s} = 1,\ldots,51, \; t = 3,\ldots,33.$$

In my estimations, Startup Survival Rate$_{\mathbf{s},t}$ is the startup survival rate (as defined in equation (1)) of state **s** in year t (e.g., March 1999 to March 2000), and Minimum Wage$_{\mathbf{s},t-2}$ is the effective (nominal) minimum wage in state **s** in year $t-2$, observed in March (e.g., March 1998), and GPI$_{\mathbf{s},t}$ is the gross personal income growth. This specification allows for state and year fixed effects. Shown are the coefficient estimates, the robust standard errors (denoted as s.e., shown in parentheses), and the associated p-values (in curly brackets). Panel A reports the full sample results over 1984 to 2014. Panel B considers sampling schemes in which I randomly divide my sample of states (i.e., the 50 states and the District of Columbia) into two groups by (i) name of the state and (ii) name of the state capital. Panel C (respectively, Panel D) considers a restricted sample in which I divide the sample of states into low and high average state GDP (respectively, low and high average union rates). The reported R^2 represents the overall R^2, and Nobs is the number of observations.

	Panel A:	Panel B:				Panel C:		Panel D:	
	Full sample	Randomization				Size		Union rates	
	1984-2014	State initials		Capital initials		Low	High	Low	High
		I	II	I	II				
β	-0.036	-0.042	-0.025	-0.042	-0.030	-0.042	-0.026	-0.043	-0.020
s.e.	(0.009)	(0.012)	(0.012)	(0.014)	(0.010)	(0.013)	(0.012)	(0.019)	(0.010)
p-val.	{0.000}	{0.001}	{0.030}	{0.004}	{0.004}	{0.001}	{0.031}	{0.022}	{0.058}
γ	0.299	0.372	0.250	0.261	0.369	0.250	0.353	0.238	0.372
s.e.	(0.031)	(0.046)	(0.037)	(0.036)	(0.049)	(0.041)	(0.037)	(0.039)	(0.051)
p-val.	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
α	-0.165	-0.155	-0.156	-0.125	-0.177	-0.151	-0.145	-0.120	-0.200
s.e.	(0.018)	(0.025)	(0.024)	(0.029)	(0.021)	(0.026)	(0.024)	(0.037)	(0.021)
p-val.	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.001}	{0.000}
R^2 (%)	74.4	73.5	76.7	72.8	76.1	72.4	78.3	73.7	74.6
Nobs	1573	803	770	801	772	803	770	801	772
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes