Federal Reserve Bank of Cleveland Working Paper Series

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Working Paper No. 19-30R

April 2022

Suggested citation: Kudlyak, Marianna, Murat Tasci, and Didem Tüzemen. 2022. "Minimum Wage Increases and Vacancies." Working Paper No. 19-30R. Federal Reserve Bank of Cleveland. https://doi.org/10.26509/frbc-wp-201930r.

Federal Reserve Bank of Cleveland Working Paper Series
ISSN: 2573-7953

Minimum Wage Increases and Vacancies*

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Abstract

Using a unique data set and a novel identification strategy, we estimate the effect of minimum wage increases on job vacancy postings. Utilizing occupation-specific county-level vacancy data from the Conference Board's Help Wanted Online for 2005-2018, we find that state-level minimum wage increases lead to substantial declines in existing and new vacancy postings in occupations with a larger share of workers who earn close to the prevailing minimum wage. We estimate that a 10 percent increase in the state-level effective minimum wage reduces vacancies by 2.4 percent in the same quarter, and the cumulative effect is as large as 4.5 percent a year later. The negative effect on vacancies is more pronounced for occupations where workers typically have lower educational attainment (high school or less) and in counties with higher poverty rates. We argue that our focus on vacancies versus on employment has a distinct advantage of highlighting a mechanism through which minimum wage hikes affect labor demand. Our finding of a negative effect on vacancies is not inconsistent with the wide range of findings in the literature about the effect of minimum wage changes on employment, which is driven by changes in both hiring and separation margins.

JEL: E24, E32, J30, J41, J63, J64.

Keywords: Minimum Wage; Vacancies; Hiring; Search and Matching.

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We thank Bezankeng Njinju, Caitlin Treanor and Thao Tran for outstanding research assistance. The views expressed here are the authors' and do not reflect those of the Federal Reserve Bank of Cleveland, Federal Reserve Bank of Kansas City, Federal Reserve Bank of San Francisco, or the Federal Reserve System.

1 Introduction

Despite decades of research, the impact of minimum wage increases on employment remains a hotly debated topic among researchers and policymakers. The long expansion after the 2007-09 recession led to the lowest unemployment rate in five decades but wage growth remained anemic and labor force participation stayed low, especially among young workers and workers with lower educational attainment. Since the last federal minimum wage increase in 2009, many states have enacted state-level changes to their minimum wage laws. Most recently, on January 1st 2022, twenty states increased their minimum wage, while the US Congress debates a similar federal-level increase.[1] A broad-based minimum wage increase might appear as an attractive labor-market-policy tool to boost wages and lower poverty among low-wage earners. However, economic theory predicts that, in a competitive labor market, a minimum wage hike might lead to a decline in employment. This issue has motivated a long-lasting, at times contentious, debate in the literature on the effect of minimum wage increase on employment (see Card and Krueger, 1994, 2000; Dube, Naidu, and Reich, 2007; Dube, Lester, and Reich, 2010; and Neumark and Wascher, 1992, 2007, 2008; among many others).

We study the effect of minimum wage increases on vacancies. To the best of our knowledge, this paper is the first study that presents empirical evidence on the effect on vacancy postings in the context of the minimum wage debate. We combine 2-digit occupation-specific county-level vacancy data from the Conference Board's Help Wanted Online at a quarterly frequency with the data on minimum wage changes at the state level. We separately estimate the effect of minimum wage increases on existing vacancies (stock) and new vacancies, i.e., less than 30-day old (flow).

We use a triple-difference identification strategy. Our identification strategy exploits the idea that different occupations can be differently impacted by minimum wage hikes due to differential mass of occupation-specific wage distributions concentrated around the prevailing minimum wage. We formalize this idea by analyzing wage distributions by occupation at the state level using micro data from the Current Population Survey (CPS). We identify occupations with large shares of employed workers at or near the state-level effective minimum wage and we refer to these occupations as "at-risk occupations." We then estimate vacancy growth in at-risk occupations relative to vacancy growth in other occupations around the time when minimum wage increase takes place in the state, and relative to growth in vacancies in at-risk occupations at the national level.

We find a statistically significant and economically sizeable negative effect of the minimum

[1] https://edlabor.house.gov/raise-the-wage-act-information

wage increase on vacancies. Specifically, a 10 percent increase in the level of the effective minimum wage reduces the stock of vacancies in at-risk occupations by 2.4 percent and reduces the flow of vacancies in at-risk occupations by about 2.2 percent.

Estimating a dynamic specification, we find that there is a strong preemptive response by firms as well as a long-lasting dynamic response. We find that firms cut vacancies up to three quarters in advance of the actual minimum wage increase. This finding is consistent with the firms' desire to cut employment and vacancies being a forward-looking tool to achieve it. This finding is also consistent with a typical announcement effect of a policy change.[2] Formally testing for the parallel trends assumption in our triple-difference identification, we find that at-risk and not-at-risk occupations do not have statistically significant differences in their vacancy trends prior to the typical announcement period. But the negative effect persists even four quarters after the minimum wage increase. The cumulative negative effect of a 10 percent increase in the minimum wage on total vacancies is as large as 4.5 percent a year later.

The large negative effect from minimum wage increases conceals substantial heterogeneity. The level of granularity in our vacancy data allows us to further distinguish occupations by skill and occupational task content. We find that vacancies in occupations that typically employ workers with lower educational attainment (high school or less) are affected more negatively than vacancies in other occupations. The negative effect on vacancy posting is exacerbated in counties with higher poverty rates, which highlights another trade-off that policymakers might want to take into account. Lastly, we do not find any significant evidence of a disproportionately more negative effect on routine jobs.

Our empirical methodology is closely related to the literature that aims to include better control groups in empirical specifications. This literature typically uses neighboring jurisdictions as controls.[3] Instead, our baseline identification strategy uses vacancies in occupations that are not in the at-risk group as a suitable control group. Since vacancies in at-risk occupations are more likely to be "treated" with a minimum wage increase, comparing vacancies in at-risk occupations to vacancies in other occupations after a minimum wage increase allows estimating a causal effect of minimum wage increases on vacancies. Our approach of identifying at-risk occupations is related to the approach of Cengiz, Dube, Lindner, and Zipperer (2019) who study the effect of minimum wage changes on employment at different points of the wage distribution. As a robustness check, we additionally implement an estimation using a contiguous-county sample as in Dube et al. (2010) and obtain results similar

[2]The mean announcement of a minimum wage increase is around 3.21 quarters prior to the actual implementation (Leung, 2021).

[3]See, for example, Card and Krueger (1994), Dube, Lester, and Reich (2010, 2016).

to our baseline results.

The focus of our analysis on vacancies versus on employment has a distinct advantage of highlighting a mechanism through which minimum wage hikes affect labor demand, and it helps sort out the debate on the effect of the minimum wage hikes on employment. Vacancies reflect the quantity of labor demanded by firms and serve as one of the adjustment margins that firms can use to reach their optimal level of employment. In contrast, employment is an equilibrium object, determined jointly by labor supply and labor demand; therefore, changes in employment reflect a combination of various margins of adjustment to a policy change. As we briefly outline below, under both the standard neoclassical and the frictional models of the labor market, minimum wage hikes lead to a decline in vacancies but the effect on employment might differ.

In the standard neoclassical models, a higher minimum wage leads to a movement to the left and up the labor demand curve (Stigler, 1946), which leads to a decline in employment. Adjustment costs might render the transition to a new employment level slow.[4] Through the lens of these models, vacancy posting costs are an implicit part of these adjustment costs, and the estimated negative effect of minimum wage hikes prior to the actual hikes is a part of the adjustment process.

In the frictional models of the labor market, where these adjustment costs are explicit, an increase in the minimum wage also leads to a decline in the number of vacancies due to an increase in the marginal cost. Our results are consistent with this theory. In contrast to the standard neoclassical models, declining vacancies do not necessarily imply lower employment in these models. The effect of the minimum wage on hiring is ambiguous because while vacancies decline, job seekers' input increases—either due to the increase in the number of job seekers or search efficiency.[5] Even though on impact one might expect a higher rate of separations due to the dissolution of some marginal matches, a higher minimum wage forces all new matches to satisfy a higher threshold for productivity. This, in turn, makes these new matches more durable relative to an environment with a lower minimum wage. One implication of this is that a minimum wage hike might lead to a decline in turnover but possibly no change in the stock variables such as unemployment and employment. This interpretation of the labor market can reconcile the negative effects of minimum wage hikes on vacancies that we find and the relatively small or non-existent effects on employment found in the literature (Allegretto, Dube, Reich, and Zipperer, 2017; Card and Krueger, 1994; and

[4]See, for example, Oi (1962); Hamermesh (1989); Diamond (1981); Acemoglu (2001).

[5]See, for example, Gorry (2013); Flinn (2006, 2011);Rocheteau and Tasci (2007, 2008); Sorkin (2015); van den Berg and Ridder (1998); Berger, Herkenhoff, and Mongey (2022); Hurst, Kehoe, Pastorino, and Winberry (2021).

Card and Krueger, 2000). More specifically, our results strongly corroborate the findings of Dube, Lester, and Reich (2016) who find significant declines in flows but insignificant effects on stocks of employment. By analyzing vacancy postings, we provide more insight into firms' behavior as they adjust to minimum wage changes. Understanding these different margins of adjustment may provide more context for policymakers and researchers on the contentious debate of the employment effects of minimum wage increases.

Our paper is related to a large empirical literature on the minimum wage debate. In addition to the literature cited above, it is related to the literature that addresses the heterogeneous effects of the minimum wage policy on different demographic groups, focusing on worker groups that are most likely to be affected, such as teenagers (Currie and Fallick, 1996), and low-wage workers (Clemens and Wither, 2019). In contrast to the earlier work by Lordan and Neumark (2018) and Aaronson and Phelan (2019), we do not find a greater negative impact on vacancies in routine or automatable occupations.

Finally, our analysis of the dynamic effects of the minimum wage increases provides insights about the firms' adjustment process through their vacancy posting behavior. Our results show a more complete picture of the labor market adjustment in response to minimum wage changes and compliment recent evidence on the dynamics of employment adjustments (Cengiz, Dube, Lindner, and Zipperer, 2019; Meer and West, 2016; Leung, 2021).

The rest of the paper is structured as follows. Section 2 presents our data. Section 3 discusses the empirical approach. Section 4 presents the main results. Section 5 presents additional results focusing on the heterogeneous effects of minimum wage increases. Section 6 summarizes several robustness exercises. Section 7 concludes.

2 Description of the Data

2.1 Minimum wage data

We construct a quarterly data set of state-level effective minimum wages during 2005-2018. We start with the state-level mandated minimum wage (if such a state mandate exists), combine this information with the federal minimum wage, and calculate the effective minimum wage for each date as the maximum of the two. We rely on the compilation of the effective minimum wage data for states and sub-state jurisdictions (such as cities and counties) in Vaghul and Zipperer (2016), which cover a period up to mid-2016. For the remainder of the sample period, we thoroughly searched for state-level minimum wage changes on the relevant state agency's websites and the information provided by the Bureau of Labor Statistics (BLS).

For our analysis, we aggregate the effective minimum wage at a daily frequency to a quarterly frequency by assigning the highest effective daily minimum wage level during the quarter to the entire quarter. In most cases though, minimum wage increases take effect at the beginning of a month and often at the beginning of a quarter.

During 2005-2018, the federal minimum wage rose from \$5.15 to \$7.25 per hour. The first hike in the federal minimum wage level during this period, in 2007, was preceded by a significant increase in the number of states with effective minimum wages above the federal level. For example, 14 states in the US had a binding state-level minimum wage, which was higher than the federal level, in 2005 (see Figure 1). Within a few years, the number of states with a binding minimum wage rose to 33 as more states enacted minimum wage laws, bringing their effective minimum wages to levels above the prevailing federal level.

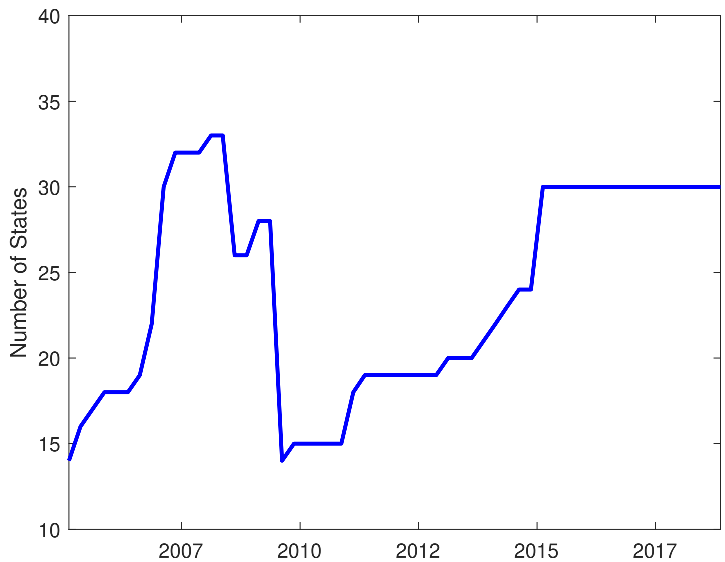

Figure 1: Number of the US States with Binding State-Level Minimum Wages
Note: The state-level minimum wage is binding if it is higher than the federal minimum wage.

The federal minimum wage has not changed since 2009, but the dispersion in the effective minimum wage across states has increased since then. As Figure 2 shows, the highest binding minimum wage at the end of 2018 stood at \$13.25 per hour in the District of Columbia, twice the level of the federal minimum wage.

There is a large variation in the magnitude of the state-level minimum wage increases as shown in Figure 3. During 2005-2018, there are 291 minimum wage hikes, ranging from 0.5 to 34 percent. The median increase is 6.5 percent and the mean increase is 7.9 percent. As described below, in our baseline approach, we consider the pool of occupations in which

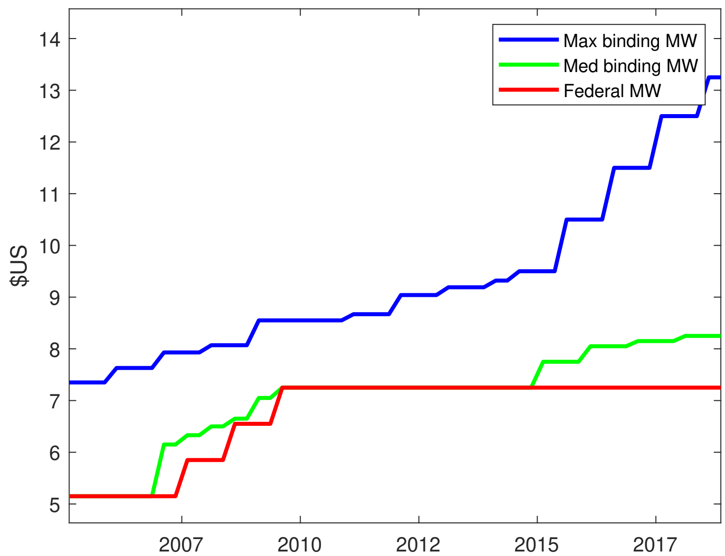

Figure 2: Range of Effective State-Level Minimum Wages

many workers earn at or below 110 percent of the prevailing minimum wage as occupations potentially vulnerable to a minimum wage increase. Almost 60 percent of all state-level minimum wage increases in our sample are below ten percent. The substantial variation in the binding minimum wage across the US states and the variation in the magnitude of the effective minimum wage changes allow us to identify the impact of minimum wage increases on vacancies.

2.2 At-risk occupations

Our identification strategy relies on an assumption that some occupations are more exposed to minimum wage increases than others. We designate an occupation as an "at-risk occupation" if a large share of workers in the occupation earn at or close to the effective minimum wage.

To identify at-risk occupations, we construct hourly wage distributions of the occupations at the two-digit level by state using micro-level data from the CPS. To construct these distributions, we use hourly wage information (from the fourth and eighth months interviews in the CPS). When hourly wage data are not available, we use weekly hours worked and weekly earnings to compute an hourly wage. We restrict our sample to employed individuals of age 16 and older, and exclude those who are self-employed or work without pay.

We then combine the constructed wage distributions by occupation at the state level

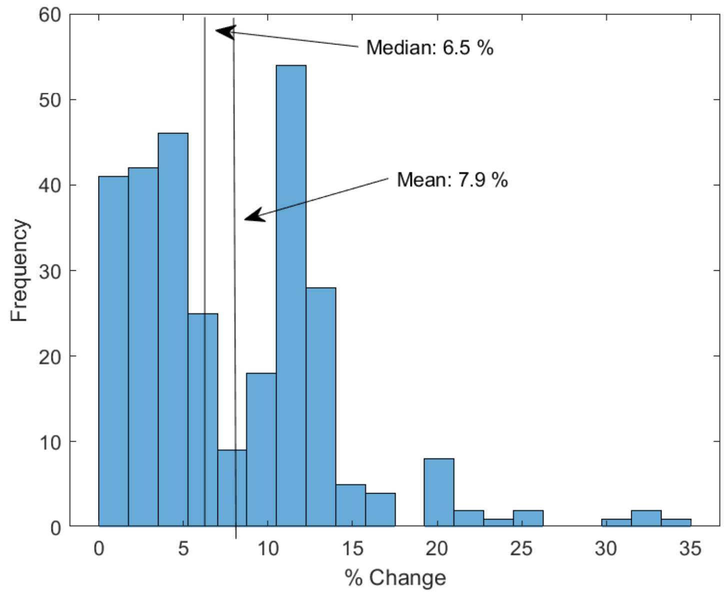

Figure 3: Distribution of State-Level Minimum Wage Increases, 2005-2018

with the data on the state-level effective minimum wage and classify each occupation in the state as "at risk" or "not-at-risk" using the following two threshold rules. First, we designate workers who earn at or below 110 percent of the effective state-level minimum wage as those who earn close to the minimum wage. The 110 percent threshold is partly informed by the distribution of the minimum wage increases shown in Figure 3. Second, we consider an occupation to be in the at-risk group, if during the entire sample period, the fraction of workers earning at or below 110 percent of the effective minimum wage is at least 5 percent. In Section 6, we show that our results are robust to variations in these two threshold levels.

First, note that our designation of an occupation as being "at-risk" does not change over time; that is, an occupation is a-risk or not-at-risk through the entire sample period. Second, analysing the at-risk occupations across states, we find that the same occupations are designated as at-risk in all states. Therefore, our designation of an occupation as at-risk is not locality-specific.

The 5 percent threshold follows naturally from the occupational wage distributions. Table 1 shows employment shares of workers in different occupations for a given year who earn at or below 110 percent of the prevailing state-level minimum wage, averaged across states. As the table shows, there is clear clustering of occupations separated by a 5 percent employment share threshold. The average share across all years is about 4.5 percent, whereas the median share is 2.8 percent.

SOC	Occupation	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
11	Management	2.3	2.8	2.1	2.4	2.2	2.0	2.5	2.3	2.3	2.4	2.3	2.2	2.6	2.6
13	Business and Financial Operations	2.1	2.0	1.8	1.7	1.6	1.4	1.6	1.5	1.4	1.5	1.7	2.1	1.6	1.8
15	Computer and Mathematical	1.5	1.8	1.6	1.4	1.3	1.2	1.3	1.5	1.4	1.6	1.2	1.7	1.4	1.3
17	Architecture and Engineering	1.8	1.6	1.2	1.3	1.2	0.9	1.3	1.3	1.2	1.3	1.6	1.6	1.3	1.7
19	Life, Physical, and Social Science Occupations	2.1	1.9	1.2	1.3	1.2	0.8	1.1	1.5	1.7	0.9	1.6	1.4	1.4	1.0
21	Community and Social Service	1.9	1.7	1.5	1.6	1.4	1.6	1.1	1.3	1.4	1.4	1.4	1.5	1.6	1.7
23	Legal	2.0	1.2	1.5	1.1	1.0	1.1	1.2	1.4	1.2	1.4	1.3	1.1	1.1	1.3
25	Education, Training, and Library	3.2	2.9	3.1	3.2	3.4	3.2	3.0	3.3	3.2	3.0	3.1	3.1	3.4	3.5
27	Arts, Design, Entertainment, Sports, Media	1.8	2.0	1.5	1.7	1.7	1.5	1.5	1.6	1.7	1.7	1.8	2.1	2.0	1.9
29	Healthcare Practitioners and Technical	1.9	2.2	1.8	1.8	1.4	1.7	1.8	1.9	1.8	1.9	2.0	2.3	2.3	2.4
31	Healthcare Support	3.2	3.5	3.6	3.5	3.1	3.2	2.9	3.4	3.2	3.6	3.8	3.4	4.0	4.5
33	Protective Service	2.2	2.4	2.3	2.3	2.7	2.9	2.7	2.3	2.8	2.4	2.6	2.8	2.9	3.0
35	Food Preparation and Serving Related	22.7	20.7	21.2	21.6	22.3	22.0	22.1	21.6	21.9	20.9	20.3	19.6	17.9	17.1
37	Building, Grounds Cleaning, and Maintenance	5.2	6.3	6.6	6.0	6.2	6.1	6.0	5.9	5.7	6.4	6.6	6.0	5.8	6.5
39	Personal Care and Service	5.5	5.9	6.3	6.4	7.1	6.4	6.4	6.6	6.4	6.5	6.6	7.1	7.3	7.3
41	Sales and Related	11.3	11.5	13.4	14.7	15.6	15.8	16.0	15.9	15.2	15.6	14.9	13.8	13.0	12.5
43	Office and Administrative Support	6.8	7.3	8.2	8.2	7.5	8.4	7.7	7.5	7.6	8.0	8.5	8.2	8.4	8.5
45	Farming, Fishing, and Forestry	4.6	4.6	4.1	3.5	3.3	3.2	3.7	3.1	3.3	3.2	3.0	3.1	4.3	3.8
47	Construction and Extraction	4.3	3.1	3.3	2.8	2.9	2.9	2.8	2.6	2.8	2.9	2.9	3.1	3.2	3.4
49	Installation, Maintenance, and Repair	2.1	2.2	1.8	1.8	2.0	2.2	2.3	2.4	2.3	2.1	2.0	2.3	2.2	2.5
51	Production	5.7	6.5	5.4	5.2	4.3	4.9	5.1	4.7	5.0	4.7	4.4	4.7	4.9	4.8
53	Transportation and Materials Moving	5.8	5.9	6.6	6.6	6.5	6.7	6.1	6.3	6.4	6.5	6.5	6.7	7.3	7.0

Table 1: Fraction of At-Risk Employment by Occupation, Averaged Across All US States

Note: Each entry shows the fraction of workers in the occupation who earn at or below 110 percent of the effective state-level minimum wage, averaged across all US states. The effective state-level minimum wage level corresponds to the geographical location of the household in the CPS. For each year, we average the fraction of employment across states and four quarters. Source: Authors' calculations using data from the CPS.

Using this approach, we identify six at-risk occupations: (1) food preparation and serving-related occupations (SOC-35), (2) building, grounds cleaning and maintenance occupations (SOC-37), (3) personal care and service occupations (SOC-39), (4) sales and related occupations (SOC-41), (5) office and administrative support occupations (SOC-43), and (6) transportation and materials moving occupations (SOC-53).

Most of the occupations in the at-risk group are low-wage service-sector jobs. Food preparation and serving-related occupations have the largest share in the at-risk pool, on average about 21 percent, followed by sales and related occupations (at 14.2 percent) and office and administrative support occupations (at 7.9 percent). Despite some variation over the years in terms of employment shares, the 5 percent rule is remarkably robust over time. None of the occupations in our at-risk group has an employment share that falls below 5 percent during the sample period. The only other occupation that satisfies this threshold in some years in our sample is production occupations (SOC-51). Our estimation results are identical when we include production occupations in our at-risk group.[6] The share of employment in the at-risk occupations constitutes about 42 percent of aggregate employment in the US in our sample.

2.3 Vacancy data

The vacancy data in our analysis come from the job openings data from the Conference Board as a part of its Help Wanted OnLine (HWOL) data series.[7] HWOL provides monthly data on vacancies at detailed geographical (state, metropolitan statistical area, and county) and occupational (six-digit SOC and eight-digit O*Net) levels starting from May 2005.[8] HWOL covers around 16,000 online job boards, including corporate job boards, and aims to measure unique vacancies by using a sophisticated deduplication algorithm that identifies unique advertised vacancies based on several ad characteristics such as company name, job title/description, city, or state. The Bureau of Labor Statistics (BLS) also publishes job openings data, the Job Openings and Labor Turnover Survey (JOLTS), which is nationally-representative. However, HWOL's detailed geographic- and occupation-level coverage makes it uniquely attractive for our analysis. JOLTS' publicly available data files do not provide data dis-aggregated below census regions and do not contain information on occupational characteristics. This additional level of granularity in the HWOL data provides us with a

[6]These results are available upon request.

[7]We use the terms "vacancy" and "job opening" interchangeably.

[8]For a detailed description of the measurement concepts and data collection methodology, see Conference Board (2017). The Conference Board Help Wanted OnLine® (HWOL) at https://www.conferenceboard.org/data/-helpwantedonline.cfm.

novel opportunity to implement our identification strategy.

We aggregate monthly data into quarterly series by constructing their quarterly averages. HWOL data include the stock of vacancies as well as new job postings (less than 30 days-old), allowing us to analyze the effects of minimum wage increases on the stock and flow of vacancies separately.

The main labor market outcome of interest in our analysis is the number of vacancies in a 2-digit occupation at the county level. There is very little variation in effective minimum wage levels at the jurisdiction level across counties within states. In rare instances where we have city level binding minimum wage laws above the state level, it is hard to map that into a county, our geographical level of detail. Therefore, we study the effect of the increase in the effective state-level minimum wage.

Table 2 shows some descriptive statistics for the county-level job openings by at-risk and not-at-risk occupational groups over time. The table shows the mean and standard deviations of the distribution of the natural logarithm of the number of total vacancies in at-risk and not-at-risk occupations across counties in each year. To construct the distributions, we sum all vacancies in at-risk occupations (SOC-35, SOC-37, SOC-39, SOC-41, SOC-43, and SOC-53) and all vacancies in not-at-risk occupations in each county. The table shows that at-risk occupations have lower levels of job openings, and a comparable (if only slightly larger) dispersion across counties relative to not-at-risk occupations for most of the sample period. About 36 percent of all job postings in our sample are in at-risk occupations.

3 Empirical Approach

3.1 Identification strategy

Our baseline empirical strategy is a triple-difference regression. We estimate the effect of the state-level minimum wage increases on the number of county-level vacancies using the following panel regression:

$$\ln V_{i,o,t} = \alpha_{i,o} + \mu_{o,t} + \gamma_{i,t} + \beta \ln(MW_{i,t}) * AtRisk_o + \varepsilon_{i,o,t} \quad (1)$$

In this specification, the outcome variable, $\ln V_{i,o,t}$, is the natural logarithm of (the number of) vacancies in county i, occupation o, and in quarter t. The variable $At\text{-}Risk_o$ is an indicator function identifying whether occupation o is an at-risk occupation, $\alpha_{i,o}$ is a county-by-occupation fixed effect, $\gamma_{i,t}$ is a county-by-time fixed effect (measured quarterly), and $\mu_{o,t}$ is an occupation-by-time fixed effect.

	At-Risk Occupations			Not-at-Risk Occupations		
Year	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.
2005	8,884	3.26	2.17	9,226	3.80	2.08
2006	12,063	3.28	2.21	12,340	3.87	2.12
2007	11,994	3.29	2.30	12,362	4.01	2.15
2008	11,980	3.33	2.28	12,401	4.11	2.10
2009	12,044	3.28	2.17	12,419	4.06	1.99
2010	12,194	3.46	2.17	12,456	4.20	2.01
2011	12,245	3.71	2.16	12,449	4.35	2.01
2012	12,370	4.02	2.06	12,488	4.57	1.98
2013	12,420	4.22	2.02	12,510	4.63	1.98
2014	12,456	4.24	2.08	12,523	4.75	1.95
2015	12,521	4.44	1.99	12,516	4.83	1.95
2016	12,506	4.40	1.94	12,520	4.78	1.95
2017	12,434	4.17	2.03	12,521	4.68	1.99
2018	12,458	4.26	1.96	12,519	4.70	1.95
All Years	168,569	3.83	2.16	171,250	4.40	2.04

Table 2: Distributions of Vacancies in At-Risk and Not-At-Risk Occupations across Counties, by Year (Vacancies in Ln)

Note: The table shows the mean and standard deviations of the distribution of the natural logarithm of the number of total vacancies in at-risk and not-at-risk occupations across counties in each year. To construct the distributions, for each county, we sum all vacancies in at-risk occupations (SOC-35, SOC-37, SOC-39, SOC-41, SOC-43, and SOC-53) and all vacancies in not-at-risk occupations.

The coefficient of interest, β, is identified from the growth of vacancies in at-risk occupations relative to other occupations in the calendar quarter when the corresponding minimum wage changes, and relative to the growth of vacancies in at-risk occupations at the national level. The power of the identification strategy comes from the ability to control for arbitrary trends in posted vacancies in the form of granular fixed effects. Note that $\ln MW_{i,t}$ and *At-Risk*$_o$ are included as an interaction term because the effect of $\ln MW_{i,t}$ without interaction is absorbed by $\gamma_{i,t}$ and the effect of *At-Risk*$_o$ is absorbed by $\alpha_{i,o}$.

For comparison, a typical empirical approach in the minimum wage literature consists of identifying a narrowly defined group (such as teenagers or restaurant workers) who are more likely to be affected by the minimum wage increase and estimating the following two-way fixed-effects regression:

$$\ln E_{i,t} = \alpha_i + \gamma_t + \beta \ln MW_{i,t} + \varepsilon_{i,t}, \tag{2}$$

where $E_{i,t}$ stands for employment in county i and at time t.

Our specification in equation (1) has several advantages over this conventional approach.

First, the specification in equation (1) controls for occupation- and county-specific trends, as well as the variation in occupational demand across locations ($\alpha_{i,o}$). As we show in Section 4.1, it is important to control for all of this variation in the vacancy data when estimating the causal effect of the minimum wage changes on vacancies. Second, our specification is equivalent to effectively running a placebo test. Specifically, there are occupations in which only a small fraction of workers are employed at wage levels that are close to a prevailing minimum wage. Legal occupations, for instance, are one such example. We find that only 1.3 percent of workers in legal occupations earn at or below 110 percent of the prevailing minimum wage throughout the sample. Hence, by essentially comparing the effects of the minimum wage increases on vacancies in at-risk occupations relative to other occupations, such as legal occupations, our empirical design provides a better identification of the causal effect of minimum wage increases on vacancies.

Our estimation relies on the variation in minimum wage across states and its disproportionate effect on occupations as defined by our at-risk categorization. As we argue in Section 2.1, there is a sizeable variation in the binding minimum wage across states. The disproportionate impact on different occupations depends crucially on the size of employment around the prevailing minimum wage in different occupations and different states. The relative effect identified by β in equation (1) mostly depends on the direct impact on the at-risk occupations. The binding minimum wage likely does not directly affect the occupations outside of our at-risk definition. We illustrate this with an example in Figure 4, which plots the cumulative wage distributions (cdf) in 2013 for two states, California (left panel) and Texas (right panel), for two occupations—(1) management and (2) food preparation and serving-related occupations. The latter occupation falls into our at-risk group and the former is within the not-at-risk occupations that constitute the control group. Compared to management occupations, food preparation and serving-related occupations have a much larger share of workers earning at or below 110 percent of the state-level binding minimum wage in both states. Compared to California, the binding minimum wage is lower in Texas in 2013 but a larger fraction of workers in food preparation and serving-related occupations earn hourly rates close to the minimum wage. In contrast, the shape of the cdfs and the relative size of the workforce susceptible to minimum wage hikes are surprisingly very similar in management occupations in both states. As this example illustrates, the number of workers in at-risk occupations can vary greatly across different states.

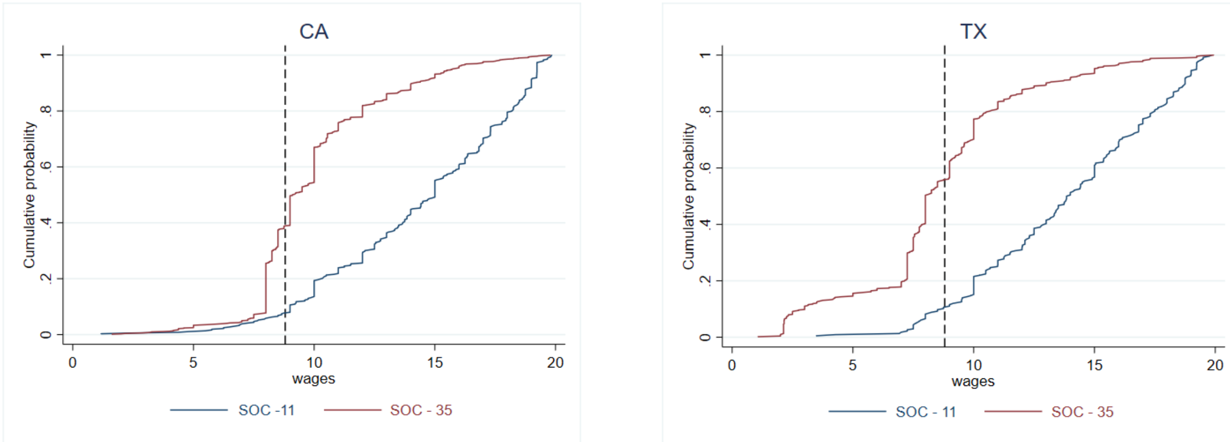

Figure 4: Variations in Wage Distributions in At-Risk and Not-At-Risk Occupations in California and Texas, 2013

Note: The figure shows the cumulative wage distribution in two different occupations (Management Occupations, SOC-11, and Food Preparation and Serving Related Occupations, SOC-35) in California and Texas in 2013. The effective minimum wage was $8 per hour in California and $7.25 per hour in Texas in 2013. The dashed lines correspond to 110 percent of the corresponding effective minimum wage in each state.

3.2 Dynamic specification

In the baseline specification, we estimate a contemporaneous effect of minimum wage increases on vacancies, as is typical in most of the related empirical literature. However, due to the forward-looking nature of the variable of interest (vacancies), and the timing of the announcement of minimum wage legislation both at the federal and state levels, we expect that there might be some forward-looking response in firms' vacancy postings behavior. To analyze this potential dynamic effect, we also estimate a distributed lag specification, where we introduce dynamic leads and lags of the change in the effective minimum wage into equation (1). Specifically, we estimate the following specification:

$$\ln V_{i,o,t} = \alpha_{i,o} + \mu_{o,t} + \gamma_{i,t} + \sum_{j=-6}^{4} \beta_j \ln(MW_{i,t+j}) AtRisk_o + \varepsilon_{i,o,t}, \tag{3}$$

Equation 3 allows us to analyze the effects of minimum wage hikes up to six quarters prior to and four quarters after the change. The cumulative effect of the change at time $t+m$ will be the sum of all β_j's up to $j = m$.

3.3 Contiguous-county approach

Finally, following the influential work by Dube, Lester, and Reich (2010), we also implement a contiguous-county specification of our main identification strategy. The main idea is to find a better control group to capture the true treatment effect of minimum wage increases. The assumption is that counties along the state borders might have more similar labor market conditions but exogenousl different state-level binding minimum wages. This specification also allows us to control for arbitrary time-varying unobserved heterogeneity between the treatment and control groups on different sides of the state border.

Specifically, in our context, implementing the contiguous-county specification implies estimating the following regression:

$$\ln V_{i,o,p,t} = \alpha_{i,o} + \mu_{o,t} + \gamma_{o,p,t} + \beta \ln(MW_{i,t}) * AtRisk_o + \varepsilon_{i,o,p,t} \tag{4}$$

where p stands for a county-pair. We still include granular fixed effects to control for local labor market conditions when using only contiguous counties along the state borders. Specifically, this sample allows us to include a county-pair-by-time-by-occupation fixed effect, $\gamma_{o,p,t}$.

4 Estimates of the Effect of Minimum Wage Increases on Vacancies

4.1 Baseline estimates

We estimate the specification in equation (1) in the panel data that we construct using HWOL and the state-level minimum wage data as described in Section 2. In the baseline specification, the unit of observation is an occupation in a county and in a particular quarter. Table 3 reports the baseline estimation results. The four columns in the upper panel report the estimated effect of minimum wage increases on total vacancies (stock) and the lower panel reports the estimated effect on new vacancies that are less than 30 days old (flow).

We find a negative and statistically significant effect of minimum wage increases on the stock of vacancies as shown in the first column of panel (a) in Table 3. Specifically, a 10 percent increase in the effective minimum wage reduces the stock of vacancies by about 2.4 percent for the at-risk occupations relative to others. To provide some context for this magnitude, consider the aggregate decline in vacancies during the 2007-09 recession. From December 2007 to June 2009, the average decline in a 2-digit occupation was around 20 percent. Considering that the 2007-09 was one of the largest economic shocks that ever hit the US economy, a decline of 2.4 percent in response to a 10 percent increase in the minimum wage is economically significant.

Columns (2) through (4) in panel (a) of Table 3 provide estimates of β in the absence of the granular fixed effects that we use in the baseline, removing one at a time. For instance,

	(a) ln (Total Vacancies)			
	(1)	(2)	(3)	(4)
ln(MW_t)*At-Risk	-0.241***	0.642***	0.226*	-0.103
	(0.083)	(0.073)	(0.120)	(0.212)
Fixed Effects:				
County x Time	Yes	Yes	Yes	
County x Occupation	Yes	Yes		Yes
Occupation x Time	Yes		Yes	Yes
Clusters	51	51	51	51
Observations	2,930,908	2,930,908	2,931,708	2,932,275
R-squared	0.921	0.913	0.840	0.898
	(b) ln (New Vacancies)			
	(1)	(2)	(3)	(4)
ln(MW_t)*At-Risk	-0.215**	0.639***	0.470***	-0.189
	(0.080)	(0.071)	(0.123)	(0.204)
Fixed Effects:				
County x Time	Yes	Yes	Yes	
County x Occupation	Yes	Yes		Yes
Occupation x Time	Yes		Yes	Yes
Clusters	51	51	51	51
Observations	2,752,397	2,752,397	2,753,617	2,754,594
R-squared	0.928	0.922	0.857	0.903

Table 3: Impact of Minimum Wage Increases on the Stock and Flow of Vacancies

Note: This table reports estimates from the OLS regressions following the specification in equation (1). Robust standard errors (in parentheses) are clustered by state. *** p<0.01, ** p<0.05, * p<0.1.

when we ignore occupational trends ($\mu_{o,t}$), the coefficient estimate becomes positive and statistically significant as shown in Columns (2). This is because, in the sample period, vacancies in at-risk occupations have a steeper upward growth trend relative to the control group of vacancies in not-at-risk occupations. One way to illustrate this is shown in Figure 5, which plots vacancy levels in management occupations versus in food preparation and servicing-related occupations over the sample period. Ignoring occupational trends biases our estimate significantly. Hence, controlling for aggregate occupational trends is crucial for our identification.

Similarly, controlling for long-run differences in county-level demand for specific occupations ($\alpha_{i,o}$) is important for identifying the true impact of the minimum wage increases on vacancies. As Column (3) in the upper panel shows, when we do not control for these differences, we obtain a statistically significant and positive effect of minimum wage increases on vacancies for at-risk occupations. On average, there are fewer vacancies in at-risk oc-

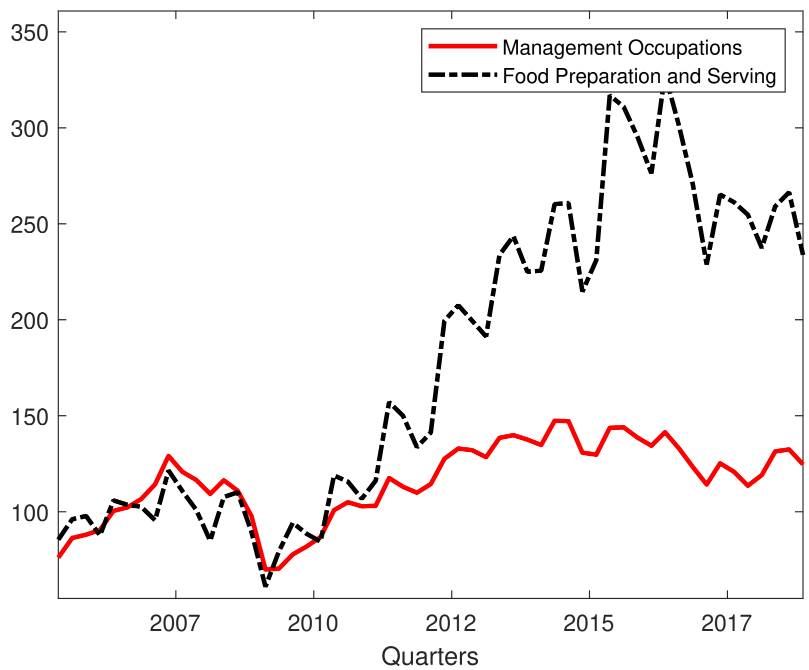

Figure 5: Trends in Vacancies in Selected At-Risk and Not-At-Risk Occupations

Note: Vacancy levels are normalized to 100 for 2006.

cupations, but county-level dispersion in these vacancies is larger compared to vacancies in not-at-risk occupations as shown in Figure 6. In general, we would get this bias if counties with more vacancies in at-risk occupations also happen to have minimum wage increases and we fail to control for this difference in demand for specific occupations. Consider, for example, Clark County in Nevada, where Las Vegas is located. The average number of vacancies in at-risk occupations was 7.3 (in ln), higher than the average number of vacancies in not-at-risk occupations, 5.9 (in ln), in our sample period. During this time, the effective minimum wage increased from \$5.15 to \$8.25 an hour in Clark County. If examples like Clark County are commonplace in our sample, ignoring county-by-occupation fixed effects will bias our estimates as Column (3) shows.

Similarly, we obtain a negative but statistically insignificant coefficient estimate when we ignore time-varying county-specific trends as shown in Column (4) of the upper panel in Table 3. Different from the earlier studies in the literature, our study is able to use county-by-time fixed effects and isolate any time-varying unobserved variation in local vacancies that are orthogonal to the time variation in the underlying minimum wage. Specifications with two-way fixed effects as in equation (2) cannot separately identify minimum wage effects and other time-varying changes at the county level. We demonstrate here that controlling

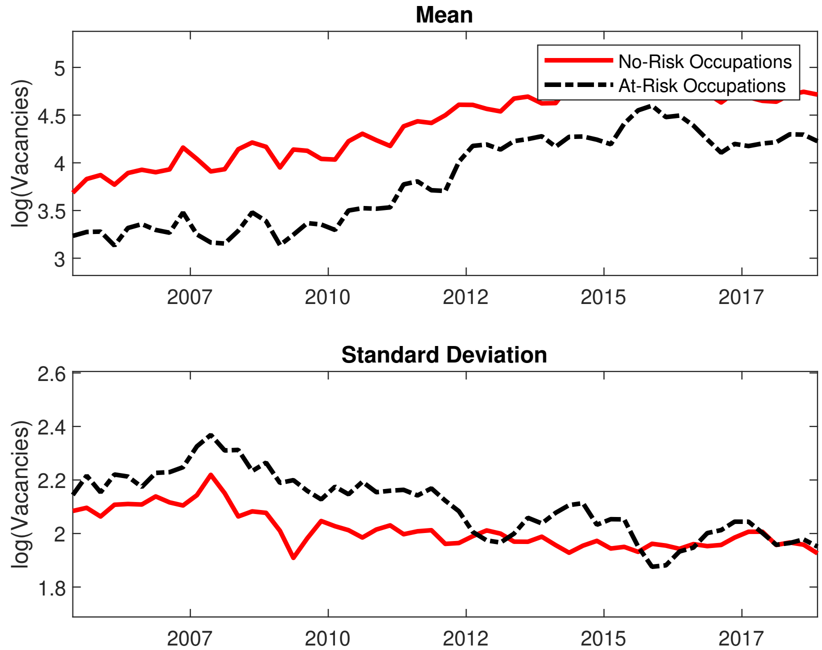

Figure 6: Mean and Standard Deviation of Vacancies in At-Risk and Not-At-Risk Occupations Across Counties, by Year

Note: The figure shows the statistics from the distribution of total vacancies across counties.

for the county-level trends is important. Our results also contribute to the debate between Allegretto et al. (2017) and Neumark et al. (2014) on the importance of controlling for local trends and preexisting differences between jurisdictions.

Finally, we repeat the above estimations for new vacancies (the flow). Similarly, we find that minimum wage increases lead to statistically significant declines in new vacancies in at-risk occupations as shown in Column (3) in the lower panel of Table 3. The magnitude of the estimate at around -0.22 is similar to the estimated coefficient for total vacancies (-0.24). Columns (2) through (4) in the lower panel show that ignoring the granular fixed effects in equation (1) introduces similar biases to the estimation results when focusing on new vacancies only.

4.2 Dynamic effects and preexisting trends

It is intuitive that vacancy posting behavior by firms has some forward-looking element. Most minimum wage increases are anticipated, and often, a legislative debate at the state level precedes the actual implementation by a few quarters.[9] Therefore, we explore whether the estimated negative contemporaneous impact of a minimum wage increase is led by a preemptive adjustment by firms before the minimum wage change comes in effect.

We are also interested in measuring the effect of minimum wage increases beyond the contemporaneous effect to examine whether some reverse causality might be at play. As Allegretto et al. (2017) point out in their critique of the methodology employed by Neumark et al. (2014), high-minimum-wage states are concentrated geographically and are usually politically left-leaning with a history of less de-unionization. Thus, if state-level minimum wages are correlated with other unobserved fundamentals that may be correlated with the evolution of vacancies, a standard two-way fixed effects specification will be ill equipped to handle the absence of parallel trends across all states. We think our triple-difference specification is much less susceptible to this as we can absorb many of these location-specific fundamentals in the set of fixed effects we use. Moreover, we can test for the presence of preexisting parallel trends with a dynamic version of our triple-difference specification.

We add dynamic leads and lags to our baseline specification and run the specification in equation 3.[10] We plot the cumulative effects in Figure 7 and Figure 8. As in Leung (2021), we set our event window between 6 quarters prior to and 4 quarters after a minimum wage increase. The cumulative effects correspond to summing up all the coefficients from the six quarters prior to the minimum wage increase up to the calendar quarter of interest. The shaded areas in the figures indicate 90 percent confidence intervals.

Figure 7 shows that the statistically significant negative effect on total vacancies starts three quarters prior to the implementation of a minimum wage increase. This reflects an announcement effect; specifically, the mean announcement of a minimum wage increase is around 3.21 quarters before implementation (Leung, 2021). We do not find much impact prior to the three quarters period, which means that the parallel trends assumption for our specification holds if we take into account the announcement effect and the forward-looking nature of the vacancies. The negative effect remains significant in the quarters following the policy change. As shown in Figure 8, the results are similar for the cumulative effects of minimum wage hikes on new vacancies.

Another way to illustrate whether the parallel trends assumption is a valid one in our context is by narrowing the focus to a subsample of states. Minimum wage changes happen at different points in time for states with a binding level that is higher than the federal level and they may be repeating multiple times in our sample period. However, there is

[9]See the following blogpost on the website of the National Conference of State Legislatures: http://www.ncsl.org/blog/2018/08/23/state-minimum-wage-developments.aspx.

[10]Individual parameter estimates are reported in the Appendix.

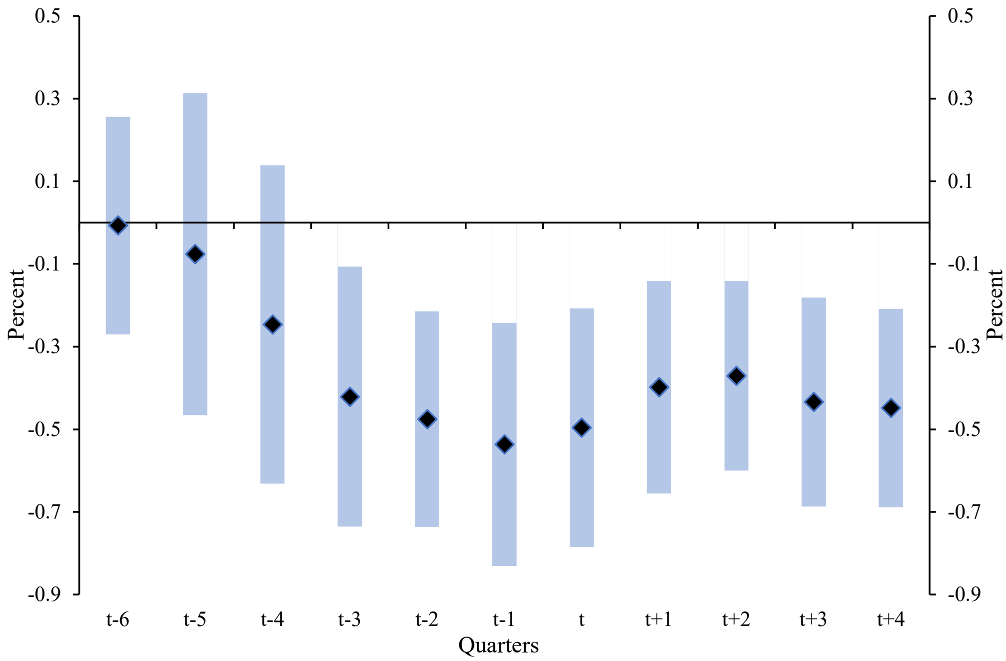

Figure 7: Estimated Cumulative Dynamic Effect of a 1 Percent Minimum Wage Increase in Quarter t on Total Vacancies

Note: The figure shows the estimated cumulative effect of the minimum wage increase in quarter t. The cumulative effects correspond to summing up all the coefficients up to the quarter of interest. The shaded areas indicate 90 percent confidence intervals.

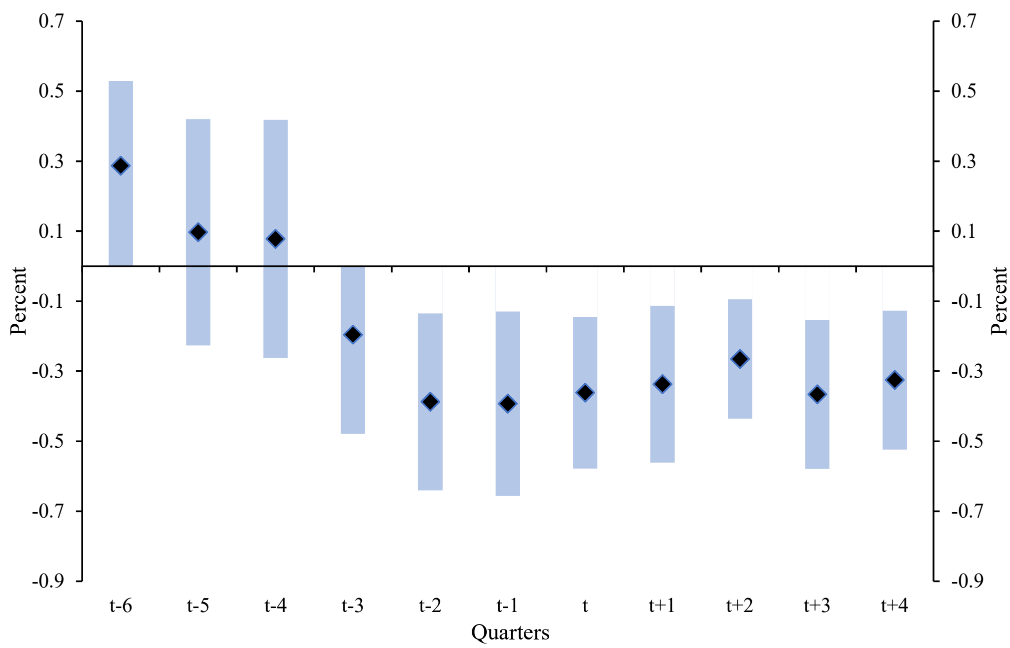

Figure 8: Estimated Cumulative Dynamic Effect of a 1 Percent Minimum Wage Increase in Quarter t on New Vacancies

Note: The figure shows the estimated cumulative effect of the minimum wage increase in quarter t. The cumulative effects correspond to summing up all the coefficients up to the quarter of interest. The shaded areas indicate 90 percent confidence intervals.

essentially one big minimum wage increase legislation at the federal level within our sample. The Fair Minimum Wage Act of 2007 increased the federal minimum wage to $5.85 per hour in July 2007 from a prior level of $5.15 per hour and put in place two more annual hikes scheduled to take effect one and two years after the initial hike.[11] Thirteen states never had a state-level minimum wage that was binding above the federal level throughout the sample period. Figure 9 plots the evolution of the vacancies in these states around the first minimum wage hike in 2007. We normalize the level of the aggregate vacancies in at-risk occupations in 2006 to that of the no-risk occupations for ease of comparison. As the figure shows, vacancies in at-risk occupations start to diverge with the minimum wage increase in 2007, possibly with a few months' lead. This is generally consistent with our baseline results and confirms that for this subsample, the parallel trends assumption clearly holds between 2005Q2 and the beginning of 2007, when the early version of the legislation passed in the US House of Representatives.

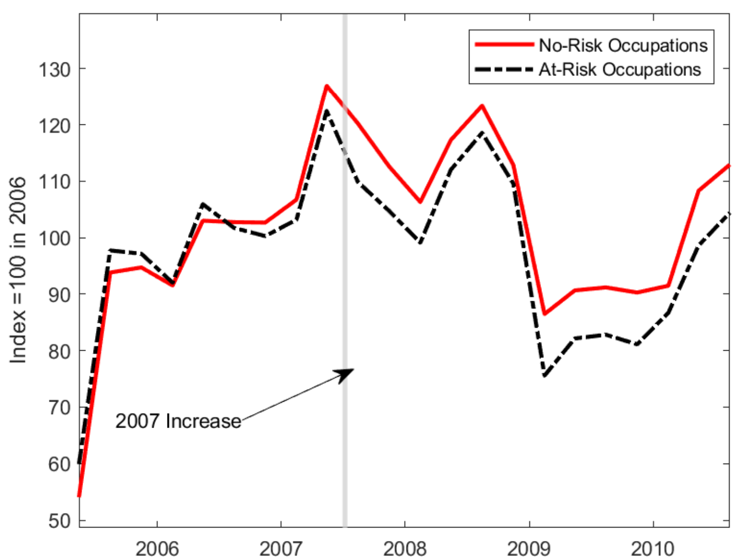

Figure 9: Parallel Trends in Vacancies by Exposure to Minimum Wage Increases

Note: The figure shows total vacancies (by exposure to minimum wage increases) in states where the effective minimum wage is the federal minimum wage.

We conclude that there is some decline in vacancies prior to the quarter when the minimum wage hike becomes effective due to the nature of adjustments by firms. However, there are no statistically significant differences between vacancies in at-risk occupations and the control group earlier than three quarters prior to the minimum wage change. This also rules

[11] The legislation proposed an increase to $6.55 per hour in July 2008 and $7.25 per hour in July 2009.

out a possible reverse causality argument such that minimum wage increases are happening in places where vacancies in at-risk occupations were already declining.[12]

4.3 Contiguous-county sample

In an influential study, Dube, Lester, and Reich (2010) propose an empirical specification to estimate the impact of minimum wage increases on employment using data from counties along the state borders. They argue that counties across the border that did not have a minimum wage change could be a better control group for those that did have a minimum wage increase. The assumption is that the unobserved heterogeneity between adjacent border counties will be less pronounced than that in the average county in each state. The authors present this approach as a general method that encompasses multiple individual case studies that had dominated part of the minimum wage literature at the time, such as Card and Krueger (1994, 2000). Motivated by these arguments, we estimate the effects of minimum wage changes on vacancies using a similar contiguous-county sample.

Although our baseline specification allows for arbitrary unobserved occupational heterogeneity at the national level, this alternative specification allows for more localized unobserved shocks to each occupation by restricting attention to contiguous counties along state borders.

Table 4 shows the estimates of equation (4) using the contiguous-county sample, which allows us to replace the occupation-by-time fixed effect with a county-pair-by-time-by-occupation fixed effect. Using this specification, we estimate a 2.5 percent decline in vacancies in at-risk occupations in response to a 10 percent increase in the effective minimum wage relative to other vacancies and compared to their neighbors (almost identical to our baseline results). For new vacancies our estimate is still large and negative, albeit with less statistical significance. We conclude that our main results are robust to having more local controls and a better control group with contiguous counties.

5 Heterogeneous Effects of Minimum Wage Increases

In this section, we explore whether the negative effect that we find for total vacancies is driven by certain characteristics of different occupations or localities. First, we explore the role of the task content of different occupations to understand if routine jobs were disproportionately more negatively affected by minimum wage hikes. Second, exploiting

[12]Moreover, when legislators debate prospective minimum wage increases, the debate does not usually focus on the relative demand in at-risk occupations, per se.

	ln (Vacancies) (1)	ln (New Vacancies) (2)
$\ln(MW_t)$*At-Risk	-0.246**	-0.187
	(0.117)	(0.122)
Fixed Effects:		
County x Time	Yes	Yes
County x Occupation	Yes	Yes
County-pair x Occupation x Time	Yes	Yes
Clusters	218	218
Observations	1,948,098	1,753,006
R-squared	0.965	0.969

Table 4: Estimated Impact of Minimum Wage Increases on Vacancies, Contiguous-County Sample

Note: This table reports coefficients from OLS regressions for the dependent variable ln(vacancies) for each occupation o, in county c of county-pair, p, and at time t (quarterly). Column (1) displays results for the stock of vacancies and Column (2) reports the regression results for new vacancies that have been posted within the past 30 days (the flow). Standard errors are clustered at the border level. *** p<0.01, ** p<0.05, * p<0.1.

educational content of the HWOL data, we turn to the educational attainment required for different occupations. Third, we investigate whether high poverty localities are affected differently by local minimum wage increases. Our results from these three exercises are summarized in Table 5.

5.1 Routine versus non-routine occupations

We examine whether the task content of an occupation matters for the vacancies' response to a minimum wage hike. For instance, a firm posting a vacancy for an occupation primarily involving routine tasks might expect a potential minimum wage increase and adopt labor-saving technologies more frequently or intensely than its competitor who seeks to hire workers for occupations with primarily non-routine tasks (Lordan and Neumark, 2018). We explore what we can learn about this question by focusing on detailed 2-digit occupations based on their skill classification.

The routine versus non-routine distinction, and a further classification into routine manual, routine cognitive, non-routine manual, and non-routine cognitive categories follow Jaimovich and Siu (2020) and Tüzemen and Willis (2013). From our list of at-risk occupations, food preparation and servicing-related occupations (SOC-35), building, grounds cleaning and maintenance occupations (SOC-37), and personal care and service occupations (SOC-39) are

	ln (Vacancies)				
	(1)	(2)	(3)	(4)	(5)
$\ln(MW_t)$*At-Risk	-0.321**		-0.256**		
	(0.133)		(0.105)		
$\ln(MW_t)$*At-Risk*RM		-0.596***			
		(0.162)			
$\ln(MW_t)$*At-Risk*C		0.037			
		(0.093)			
$\ln(MW_t)$*At-Risk*NRM		-0.321**			
		(0.133)			
$\ln(MW_t)$*At-Risk*R	0.149		-0.284		
	(0.139)		(0.180)		
$\ln(MW_t)$*Low Education				-0.376**	
				(0.179)	
$\ln(MW_t)$*At-Risk*P06					-0.016***
					(0.004)
Fixed Effects					
County x Time	Yes	Yes	Yes	Yes	Yes
County x Occupation	Yes	Yes	Yes	No	Yes
Occupation x Time	Yes	Yes	Yes	No	Yes
County x Education	No	No	No	Yes	No
Education x Time	No	No	No	Yes	No
Clusters	51	51	51	51	51
Observations	2,930,908	2,930,908	1,230,872	1,147,991	2,360,686
R-squared	0.921	0.921	0.923	0.943	0.916

Table 5: Heterogeneous Effects of Minimum Wage Increases on Vacancies

Note: The table reports estimates from the OLS regressions for the dependent variable ln(vacancies) for each occupation o, in county c at time t (quarterly). The interaction term Routine (R) indicates whether the occupation is a routine one. RM, RC, and NRM, refer to a finer classification of 2-digit occupations by task content, where R stands for Routine, M for Manual, C for cognitive and NR for Non-Routine. The omitted occupational group in Column (1) is the non-routine cognitive group (SOC-11 through SOC-29). Note that this group does not include any at-risk occupations. Columns (1) and (2) report the results by task content. Column (3) presents the result for educational attainment level by occupation and the last column presents our results related to local poverty rate (County level poverty rate in 2006 - P06). Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1 .

considered non-routine manual (NRM) occupations. Sales and related occupations (SOC-41), and office and administrative support occupations (SOC-43) constitute the routine cognitive (RC) group. The only at-risk occupation in the routine manual (RM) category is transportation and materials moving occupations (SOC-53). There is no at-risk occupation in the non-routine cognitive (NRC) group. This particular categorization poses an additional identification issue for us. Since *all* of the RC occupations and *none* of the NRC occupations are in the at-risk group, when we pool cognitive and manual occupations together, we cannot distinguish the minimum wage effects from those that are associated with the routine versus non-routine distinction.

We interpret the regression results shown in Column (1) of Table 5 with this caveat in mind. The variable of interest, ln(MW_t)*At-Risk*R, captures the additional marginal effect of the minimum wage increases on routine jobs. The coefficient estimate we obtain is statistically insignificant, suggesting that beyond the first-order effects on the at-risk occupations, there are no additional negative effects on routine jobs. However, the result still suggests a significant negative impact on at-risk routine occupations, implying a 1.72 percent decline in vacancies in this group in response to a 10 percent rise in the minimum wage.

5.2 Manual versus cognitive occupations

We can further divide the routine and non-routine occupations into manual and cognitive categories as we do in Column (2). Note that because of the identification issue we explained above, we cannot include ln(MW_t)*At-Risk*R or the NRC indicator in this specification.

Based on the regression results reported in Column (2) manual occupations seem to be disproportionately more negatively affected by the minimum wage increases, not the routine jobs, which is in contrast to the results in Lordan and Neumark (2018). However, this is misleading, given the perfect correlation between an occupation's at-risk status and routine task content among cognitive occupations. To circumvent this identification problem, in Column (3) of table 5, we report the regression result for the interaction term ln(MW_t)*At-Risk*R in the subsample of manual occupations, which identifies the marginal impact of an increase in the effective minimum wage on routine jobs among at-risk occupations. As we lose a lot of observations by restricting to only manual occupations, the estimated coefficient is not as precisely estimated, suggesting a somewhat negative effect on routine jobs (at -0.284). Hence, our results are different from those in (Lordan and Neumark, 2018) and do not show more adverse effects of minimum wage increases on vacancies in occupations with predominantly routine tasks.

5.3 Role of education

Next, we turn to the role of education. The Conference Board's HWOL data provide us with a convenient mapping from a subset of the occupational data into an education code that matches with the predominant education level for workers in that occupation. This information is not necessarily based on the content of the online posting but is assigned using the occupational coding from the BLS.[13] The HWOL data aggregates total vacancies in each county into eight educational groupings based on this BLS mapping. Since the educational groupings do not correspond to two-digit SOC codes, we cannot use at-risk status as a source of variation that interacts with education. However, educational codes are bound to reflect more granular detail at the occupation level. It would be very coarse to assume, for instance, that all workers in office and administrative support services occupations have lower educational attainment. The education codes rely on finer SOC level information and assign the low-education level to a subset of vacancies for the whole 2-digit sector.

Given this difference in identifying occupations, we maintain a triple-difference regression design by estimating the effect of minimum wage increases on vacancies by required educational attainment. More specifically, we use an indicator function, Low Education, which equals 1 if the vacancy is assigned to an education level of high-school or less, and interact it with the effective minimum wage.

Workers who are more susceptible to the adverse effects of minimum wage hikes are naturally low-wage workers. If low-wage workers are more likely to be employed in occupations that do not require high levels of educational attainment, then we might expect to see more adverse effects from minimum wage increases on these occupations. In Column (3) of table 5, we see that this is indeed the case. We find that a 10 percent minimum wage increase reduces low-education vacancies by about 3.8 percent.

5.4 Local poverty levels

Finally, we explore whether our estimated elasticity of vacancies with respect to minimum wage changes is correlated with poverty at the local level. The minimum wage debate is often framed by policymakers as a tool to combat poverty and elevate family incomes. Recent research shows that minimum wage increases have a significant positive effect on the non-elderly poverty rate in the US (Dube, 2019). We ask a different question: Do counties with higher poverty rates suffer similar declines in job openings relative to places

[13] The BLS assigns a typical level of education needed for entry into an occupation and has eight different categories; see https://www.bls.gov/emp/documentation/education/tech.htm.

with lower poverty rates? We do not want to confound our analysis, so instead, we take the poverty rate at the beginning of the sample as given for each county and interact it with the elasticity we estimate in the baseline. More formally, we report the coefficient estimate for the interaction term ln(MW$_t$)*At-Risk*P06 in the last column of table 5, where P06 stands for the county-level poverty rate in 2006.

We find that counties with higher poverty rates experience disproportionately larger declines in vacancies. Based on the 2006 poverty rate distribution, the poverty rate in the first quintile was 10.2 percent and in the fourth it was 19.2 percent. Hence, our estimate from Table 5 implies an inter-quintile difference of about a 1.4 percentage point larger decline in vacancies in response to a 10 percent increase in the minimum wage. This significant result suggests another channel through which underlying poverty might be associated with job openings in the context of the minimum wage debate. While research shows that higher minimum wages reduce non-elderly poverty rates (Dube, 2019), our results imply that this might happen at the expense of fewer job opportunities for those locales.

6 Robustness

Our results clearly show that minimum wage increases lead to a large and significant decline in job openings for at-risk occupations. Our definition of at-risk occupations relies on two thresholds that we chose. Even though we think we have good arguments for the legitimacy of the thresholds, we analyze how robust our results are to changes in these thresholds in this section. We also examine how a particular measurement issue in the vacancy data may affect our results and whether minimum wage changes at the federal level have a different impact relative to state-level changes that bind.

Since our identification strategy is ultimately about the categories of at-risk occupations, one simple way to check for the robustness of our results with respect to this definition is to remove occupations in the at-risk group one at a time and rerun our baseline regression. Note that this, in a sense, is a test of the robustness of our 5 percent threshold. Dropping building, grounds cleaning, and maintenance occupations, for instance, effectively brings the threshold to 6.5 percent from 5 percent.

Figure 10 presents point estimates and the 95 percent confidence intervals around them as we remove occupations from the at-risk group one at a time. None of these exclusions change our baseline result. The smallest elasticity we get falls to -0.17 (when transportation and materials moving occupations are excluded) and even then, our baseline estimate of -0.24 falls into the confidence band. Hence, we conclude that our baseline results are robust to variations in our baseline definition of the at-risk occupation group.

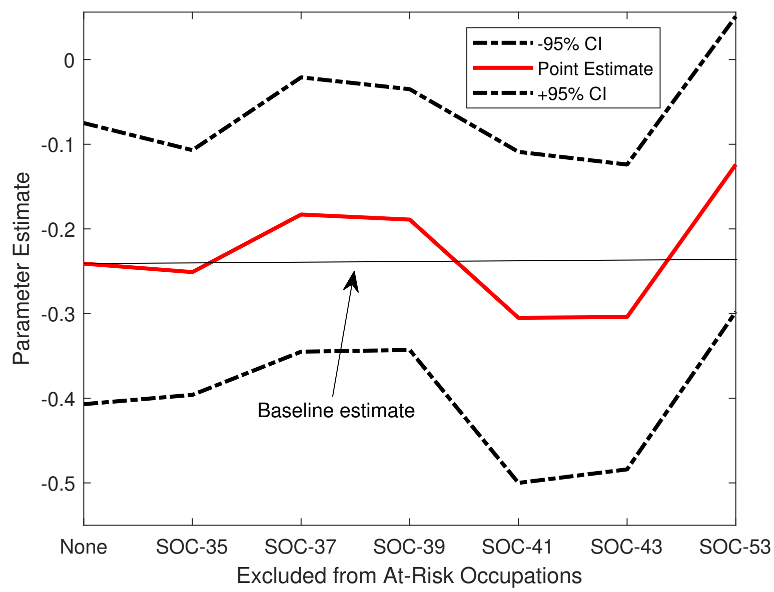

Figure 10: Robustness Results I

Note: The figure shows the parameter estimates from the baseline specification with at-risk occupations removed from sample one by one and the 95 percent confidence intervals. Horizontal line indicates the baseline estimate with all six occupations in the at-risk definition.

Another potentially unique challenge in our analysis is posed by the nature of the HWOL data at the granular level that we use. In principle, there may not be any vacancies posted for a certain 2-digit occupation category in a sparsely populated county in our sample. In fact, this is somewhat common. Since we take the logarithmic transformation of the vacancy data, zeros will drop out from the sample. Incidentally, if in the following quarter this is followed by one posting, that county-occupation observation will be back in the sample. Hence, one might worry that we are getting some spurious correlations driven by these somewhat arbitrary changes. We can test how robust our results are to this measurement issue with two possible alternatives. We present these two alternatives along with the baseline result for convenience in Table 6.

The first alternative is to transform the level of vacancies by the inverse hyperbolic-sine function. This transformation avoids dropping zero observations from our estimation sample. As Column (2) shows, this amounts to an additional 1 million observations, quite a large increase relative to the baseline. However, it barely affects our baseline result, yielding to a very similar estimate of -0.25. Another transformation we consider is effectively re normalizing the zero observation by using $\ln(V_{i,o,t}+1)$ for the outcome variable, instead of $\ln(V_{i,o,t})$. This transformation also does not change the main conclusion, as Column (3) of

	ln (V)	$\ln(V + \sqrt{V^2+1})$	ln(V+1)	ln (V)
	(1)	(2)	(3)	(4)
$\ln(MW_t)$*At-Risk	-0.241***	-0.250***	-0.227***	-0.361***
	(0.083)	(0.085)	(0.077)	(0.103)
$\ln(MW_t)$*At-Risk*FedMW				-0.022
				(0.017)
Fixed Effects				
County x Time	Yes	Yes	Yes	Yes
County x Occupation	Yes	Yes	Yes	Yes
Occupation x Time	Yes	Yes	Yes	Yes
Clusters	51	51	51	51
Observations	2,930,908	3,974,630	3,974,630	2,930,908
R-squared	0.921	0.941	0.950	0.914

Table 6: Robustness Results II

Note: The table reports estimates from the OLS regressions for three different transformations of the dependent variable, vacancies for each occupation o, in county c, and at time t (quarterly). The first column reports the baseline results, the second column shows results when we use a transformation with an inverse-hyperbolic sine function, and the last column shows results when we re-normalize "zero" observations by adding 1 before logarithmic transformation. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 6 shows. We conclude that our results are robust to this particular measurement issue in the vacancy data.

The last column in Table 6 addresses a question of whether minimum wage changes have a different effect if the binding minimum wage is due to an increase at the federal level. The question arises because there might be some unobserved factors that determine whether states choose to have a state-level minimum wage that is binding. In other words, whether or not a jurisdiction has a binding level for the minimum wage that differs from the federal one may not be random (Allegretto et al., 2017). To address this question within our empirical approach, we modify the baseline regression with an additional interaction term, where we allow for a different effect on vacancies if the binding minimum wage was a federal change (FedMW dummy in Table 6). The estimates reported in Column (4) show that this was not a significant channel.

7 Conclusion

We use a unique data set and propose a novel identification strategy to estimate the impact of minimum wage increases on labor demand as measured by vacancies, a labor market outcome variable that has not been studied in the large empirical minimum wage literature.

Our identification strategy builds on the idea that not all occupations are similarly affected by minimum wage increases. A much larger fraction of workers earn at or near the prevailing minimum wage level in some occupations than in others. Intuitively, one would expect these occupations to be affected differently by a minimum wage increase. We formalize this idea by identifying six 2-digit occupations as potentially at-risk occupations.

Our results show statistically significant and large negative effects of minimum wage increases on vacancies in at-risk occupations. More specifically, vacancies in at-risk occupations drop by 2.4 percent in response to a 10 percent rise in the prevailing minimum wage relative to other occupations. This baseline result is driven by a strong preemptive response by firms cutting vacancies in advance of the minimum wage change. Furthermore, the decline in vacancies is larger for occupations that generally employ workers with lower educational attainment and those in counties with higher poverty rates.

The literature on the employment effect of minimum wage increases has been contentious, arguing for different empirical designs and delivering sometimes starkly different estimation results. On the one hand, studies that use cross-geographical variation with fixed effects mostly point to somewhat small but statistically significant negative effects (Neumark and Wascher, 1992, 2007). On the other hand, event studies involving neighboring jurisdictions that focus on individual minimum wage episodes (Card and Krueger, 1994, 2000; Dube et al., 2007) or consider a whole set of them (Dube et al., 2010) find no significant negative effects on employment. We show that both methodologies provide consistently negative and significant effects for the case of vacancies. Either using cross-county variation along with occupational heterogeneity in terms of exposure to minimum wage hikes or relying on an adjacent-border-county regression specification provide us with similar estimation results.

We argue that our results corroborate those of Dube et al. (2016) and provide estimates that are consistent with a frictional view of the labor markets. Specifically, vacancies drop in response to minimum wage increases. At the same time, the effect of minimum wage increases on employment (a stock variable) might be insignificant due to potentially offsetting effects on the hiring and separation margins operating via changes in the profitability of matches.

Appendix A Estimates of the Dynamic Specification

This appendix provides the parameter estimates in the empirical specification with dynamic leads and lags expressed in equation 3, used to calculate the cumulative effects in Figures 7 and 8.

	ln (Vacancies) (1)	ln (New Vacancies) (2)
β_{t-6}	-0.007	0.287**
	(0.157)	(0.144)
β_{t-5}	-0.069	-0.190*
	(0.126)	(0.107)
β_{t-4}	-0.170**	-0.019
	(0.084)	(0.100)
β_{t-3}	-0.175	-0.274
	(0.167)	(0.183)
β_{t-2}	-0.054	-0.192*
	(0.128)	(0.112)
β_{t-1}	-0.061	-0.005
	(0.080)	(0.074)
β_{t}	0.041	0.032
	(0.078)	(0.070)
β_{t+1}	0.097	0.024
	(0.060)	(0.065)
β_{t+2}	0.028	0.071
	(0.065)	(0.095)
β_{t+3}	-0.063	-0.101
	(0.093)	(0.071)
β_{t+4}	-0.014	0.041
	(0.088)	(0.083)
Fixed Effects:		
County x Time	Yes	Yes
County x Occupation	Yes	Yes
Occupation x Time	Yes	Yes
Clusters	51	218
Observations	2,930,908	2,268,322
R-squared	0.921	0.932

Table A1: Estimated Dynamic Impact of Minimum Wage Increases on Total and New Vacancies

Note: This table reports coefficients estimates for the specification expressed in equation 3. Column (1) reports the results when the dependent variable is ln(vacancies) in each occupation o, in county c, and at time t (quarterly). Column (2) displays results for new vacancies that have been posted within the past 30 days (flow). Standard errors are clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1.

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