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Marianna Kudlyak, Murat Tasci, and Didem Tüzemen

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Federal Reserve Bank of Kansas City

Minimum Wage Increases and Vacancies

Marianna Kudlyak
Federal Reserve Bank of San Francisco

Murat Tasci
Federal Reserve Bank of Cleveland

Didem Tüzemen
Federal Reserve Bank of Kansas City

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Abstract

We estimate the impact of minimum wage increases on the quantity of labor demanded as measured by firms' vacancy postings. We use propriety, county-level vacancy data from the Conference Board's Help Wanted Online to analyze the effects of minimum wage on the quantity of labor demanded. Our identification relies on the disproportionate effects of minimum wage hikes on different occupations, as the wage distribution around the binding minimum wage differs by occupation. We find that minimum wage increases during 2005-2018 period has led to substantial declines in vacancy postings in *at-risk occupations*; occupations with a larger share of employment around the prevailing minimum wage. Our estimate implies that a 10 percent increase in the binding minimum wage level reduces vacancies by 2.4 percent in this group. The negative effect is concentrated not exclusively in the routine jobs, but more in the manual occupations.

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

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

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1 Introduction

Despite decades of research, the minimum wage remains a hotly debated issue among researchers and policymakers. The issue is presently at the forefront, a decade after the Great Recession. Before the COVID-19 pandemic, while the unemployment rate remained at its lowest level in five decades, wage growth remained anemic and labor force participation was low by the standards of recent history, especially among young and lower skilled workers. A broad-based minimum wage increase presents itself as an attractive labor market policy tool to boost wages. In a competitive labor market, theory predicts that this might happen at the expense of a loss in employment. This issue motivated a large literature on the effects of minimum wage hikes on employment (see Card and Krueger (1994, 2000), Neumark and Wascher (1992, 2007, 2008), among others).

This paper contributes to this literature in several ways. In contrast to the rest of the literature, we provide evidence for the effect of minimum wage changes on vacancies, an important labor market variable of interest. We use vacancy data at the county level for 2-digit occupation groups at a quarterly frequency to study the effect of minimum wage increases. Our identification strategy relies on the assumption that some occupations are less vulnerable to minimum wage increases than others. We formalize this identification by analyzing the wage distribution by occupation at the state level from Current Population Survey (CPS).[1] Based on our analysis of occupational wage distributions, we identify several occupations with mean wages close to the minimum wage, that we refer to as *at-risk occupations*. Our empirical specification relies on identifying the growth in vacancies for at-risk occupations relative to others around the time when minimum wage changes in that state and relative to the growth in national vacancies in the at-risk occupation group.

We find significant negative effects, implying that a 10 percentage increase in the level of a binding minimum wage reduces vacancies in at-risk occupations by about 2.4 percent. Our

[1] This approach is related to recent work by Cengiz et al. (2019), where authors explore the effect of minimum wage changes at different points of the wage distribution.

results seem to be robust to more specific local controls as we find almost identical estimates using adjacent border counties (as in Dube et al., 2010). Moreover, we find that this baseline result is driven by strong preemptive response by the firms, cutting vacancies in advance of the minimum wage change. Lastly, we find strong evidence that manual occupations, rather than routine ones, among the at-risk group are behind the significant negative effect found in the baseline.

Section 2 provides an overview of some recent literature. Section 4 discusses our data in detail. Section 4 presents our empirical approach and baseline estimates. Section 5 presents robustness exercises and Section 6 concludes.

2 Minimum Wage and Vacancies in the Related Literature

2.1 Theory

In both the standard neoclassical and frictional models of the labor market, the increase in the minimum wage leads to a decline in the quantity of labor demanded, unless the labor demand for minimum wage jobs is inelastic. In the standard neoclassical models, a higher minimum wage leads to movement to the left and up the labor demand curve (Stigler, 1946), which leads to a rapid decline in employment. Adjustment costs might render the transition to a new employment level slow (Oi, 1962; Hamermesh, 1989; Diamond, 1981; Acemoglu, 2001). In the frictional models of the labor market, an increase in the minimum wage also leads to a decline in the number of vacancies due to an increase in the marginal costs. The effect of the minimum wage on hiring (i.e., job creation) is ambiguous because while vacancies decline, the job seeker input increases - either due the increase in the number of job seeker or search efficiency (van den Berg and Ridder, 1998; Flinn, 2006, 2011; Rocheteau and Tasci, 2007, 2008; Gorry, 2013; Sorkin, 2015).

Recent models allow for studying richer effects of the minimum wage increases by allowing capital-labor substitutability. Hémous and Olsen (2016) show that increases in the cost of low-skill labor leads to an increase in automation which in turn increases the demand for high-skill workers but reduces the demand for low-skill workers. Bauducco and Janiak (2018), using a calibrated search and matching model, find that a relatively large increase in the minimum wage leads to a decrease in employment but to an increase in capital and output.

2.2 Empirics

Empirical literature has primarily focused on the effect of the minimum wage on employment. The literature is highly contentious, with the estimates ranging from zero (Card and Krueger, 1994) to large negative effects (Neumark and Wascher, 2008).

Estimation of the effect of state-level minimum wage hikes presents a few challenges. The state-level real minimum wage hikes have a "saw tooth" pattern because nominal minimum wage hikes are eroded by inflation over time (Neumark and Wascher, 1992). This saw-tooth pattern, adjustment costs and long-run planning horizons complicate the analysis. Recently, Meer and West (2016) argue that the minimum wage hikes might affect not necessarily the level but the growth of employment.[2] They argue that the effect on the level of employment is confounded by adjustment costs and existing approaches in the literature are stacked against finding an effect on employment. They find that an unequivocally higher minimum wage leads to a lower rate of job growth. In particular, a 10 percent increase in the minimum wage causes a half percentage point reduction in the rate of job growth. The effect is not permanent though as it gets eroded by inflation and increases in the state's comparison group. They also find that most of the decline in the net job growth is driven primarily by reduction in job creation by contracting establishments as opposed to increases in job destruction by contracting establishments. The effect on vacancies that we study is at the core of this margin.

A large literature focuses on the effects of minimum wage increases on worker groups

[2] Building on the treatment effects studies (Lee and Solon, 2011; Wolfers, 2006), Meer and West (2016) argue that if the treatment effect is not a discrete level shift in employment on impact but rather a change in the slope (i.e., in the rate of net employment growth), then studies that control for jurisdiction-specific trends might suffer from an attenuation bias.

that are most likely to be affected – teenagers, low-skill or low-wage workers. For example, Clemens and Wither (2019) estimate the effect of minimum wage increases on low-skilled workers' employment and income trajectories and find that binding minimum wage increases had significant, negative effects on the employment and income growth of targeted workers. On the other hand, Currie and Fallick (1996) focus on the reemployment probabilities of the youth in NLSY to estimate the employment effect of the minimum wage changes in 1979 and 1980 for low-wage workers.

Recently, studies focus on the heterogeneity of the effect across types of jobs. Technological advances and the decline in the price of labor-substituting technology have made capital cheap relative to substitutable labor. Lordan and Neumark (2018) find that increasing the minimum wage decreases significantly the share of automatable employment held by workers with a high school diploma or less. They also find that job opportunities improve for high-skill workers in the industries where a high share of low-skill workers employed are in automatable jobs. That is, a minimum wage increase spurs substitution away from low-skill workers in automatable jobs. Aaronson and Phelan (2019) find that increases in the cost of low-wage labor, via minimum wage hikes, lead to relative employment declines at routine cognitive occupations but not routine manual or non-routine low-wage occupations. This suggests that low-wage routine cognitive tasks are susceptible to technological substitution. While the short-run employment consequence of this reshuffling on individual workers is economically small, due to concurrent employment growth in other low-wage jobs, workers previously employed in routine cognitive jobs experience relative wage losses.

Other authors study the impact of the minimum wage increases on other important aspects of labor relationships. Aaronson, French and MacDonald 2008 find that restaurant prices unambiguously rise after minimum wage increases are enacted. Other aspects include quality of newly created matches, job ladder dynamics, etc.[3] Our paper addresses some of this underlying heterogeneity by addressing the differential effects on different types of

[3] See Flinn (2006) and Neumark and Wascher (2008) for detailed reviews.

occupations by their routine-task content.

3 Description of the Data

3.1 Vacancy Data

Our main labor market outcome variable is the county-level vacancy (job opening) data reported by the Conference Board (2017) as part of its Help Wanted OnLine (HWOL) data series. HWOL provides a monthly snapshot of the quantity of labor demanded at detailed geographical (state, metropolitan statistical area, and county) and occupational (six-digit SOC and eight-digit O*Net) levels since May 2005.[4] For the period in question, HWOL represents the bulk of the advertised job openings, as print advertising declined in importance.[5]

HWOL covers roughly 16,000 online job boards, including corporate job boards, and aims to measure unique vacancies by using a sophisticated deduplication algorithm that identies unique advertised vacancies based on several ad characteristics such as company name, job title/description, city, or state. HWOL is not the only source of data on job openings, though. The Bureau of Labor Statistics (BLS) publishes nationally representative data, the Job Openings and Labor Turnover Survey (JOLTS), which also measures vacancies. However, HWOL's detailed geographic- and occupation-level coverage makes it uniquely attractive for our analysis. JOLTS' publicly available data files do not have more detailed coverage than census regions and lack any information on occupational characteristics. This additional level of granularity in the HWOL data provides us with a novel opportunity to implement our identification strategy.

The sample period for the HWOL data we use in this paper ranges from May 2005 to October 2018. This provides us with the coverage of the time-period with various minimum

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

[5] In fact, HWOL started as a replacement for the Conference Board's Help-Wanted Advertising Index of print advertising.

wage increases at the state and federal levels. Even though we have data at the monthly frequency, in this paper, we focus on the quarterly data, aggregated from the monthly series. 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 stocks and flows separately.

Our identification strategy relies on identifying occupations that have a large mass near the prevailing minimum wage in the wage distribution. We describe this process in detail below (in section 3.3). This process yields to a set of 2-digit occupations that we indicate as at-risk occupations. These occupations are: Food processing and servicing related occupations (SOC-35), building and grounds cleaning and maintenance occupations (SOC-37), personal care and service occupations (SOC-39), sales and related occupations (SOC-41), office and administrative support occupations (SOC-43) and transportation and material moving occupations (SOC-53). The overall share of employment in these occupations constitutes about 42 percent of aggregate employment in the U.S., slightly higher than the share of vacancies posted.

Throughout our sample period, about 36 percent of all job postings are for occupations that fall into the at-risk group of occupations, which are more susceptible to minimum wage hikes. Table 1 shows some descriptive statistics for the vacancy data over time by occupational group. We see that at-risk occupations have lower levels of job openings over the entire sample. However, vacancies in both at-risk and no-risk occupations present a procyclical pattern over the business cycle, slightly declining during the recession and rising over the course of the expansion.

3.2 Minimum Wage Data

We construct a quarterly data set of state-level effective minimum wages. To construct this, 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 a maximum of the two. We heavily rely on the compilation of the

Table 1: DISTRIBUTION OF VACANCIES BY OCCUPATION – COUNTY LEVEL

	At-Risk Occupations			No-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

Note: This table presents the first and second moments for vacancies at the county-level over time. We sum all vacancies within occupations that are in the at-risk group (SOC-35, SOC-37, SOC-39, SOC-41, SOC-43, and SOC-53) and present the log of that sum. Similarly for the reminder of the occupations that are not in the at-risk group.

effective minimum wage data for states and sub-state jurisdictions (such as cities and counties) in Vaghul and Zipperer (2016). Their sample ends in mid-2016. For the remainder of the sample period, we thoroughly searched for state-level effective minimum wage changes on the relevant state agency's websites and the information provided by the BLS.

The primary data from Vaghul and Zipperer (2016) are available at the daily frequency to specifically identify the effective date of minimum wage change. When we aggregate our minimum wage measure to the quarterly frequency, we assume the higher minimum wage level as the binding one for the quarter. Our results are robust to slightly different variants of this aggregation. Moreover, in most cases, minimum wage increases take effect at the beginning of a month and often times at the beginning of a quarter.

As Figure 1 shows, our sample period covers significant variation in effective minimum wages at the state-level. Early in our sample period, the federal minimum wage rose gradually from \$5.15 per hour to \$7.25 per hour. The first hike in the federal minimum wage level in

2007 was preceded by a significant decline in the number of states with effective minimum wages at the federal level. At the beginning of the sample in 2005, there were 37 states in the U.S. which did not have a binding state-level minimum wage. Within a few years, this number declined to 18 as more states enacted minimum wage laws bringing their effective minimum wages to levels above the prevailing federal level. The federal minimum wage has not changed since 2009, but the state level variation, if anything, increased since then. As Figure 2 shows, the highest binding minimum wage at the end of 2018 stood at $13.25 per hour (in DC), twice the level of the federal minimum wage.

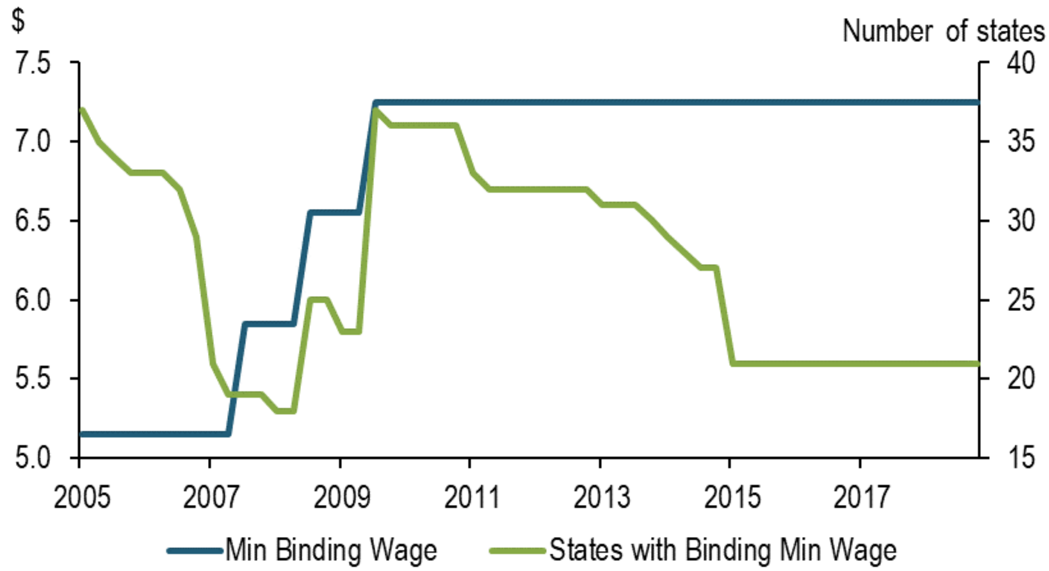

Figure 1: Federal minimum wage level and the number of states that have a binding minimum wage level that is higher than the federal one.

There is a large geographical variation in the level of the minimum wage, as well as a sizeable variation in the magnitude of changes in our sample. There are about 300 effective minimum wage hikes in our data, ranging between a 0.5 percent increase to more than 34 percent increase. The median percent change in the effective minimum wage is right around 7 percent. In our baseline identification, we consider the pool of workers who earn at or below 110 percent of the prevailing minimum wage in a specific location, as potentially vulnerable workers to a minimum wage increase. Almost 60 percent of all minimum wage increases in

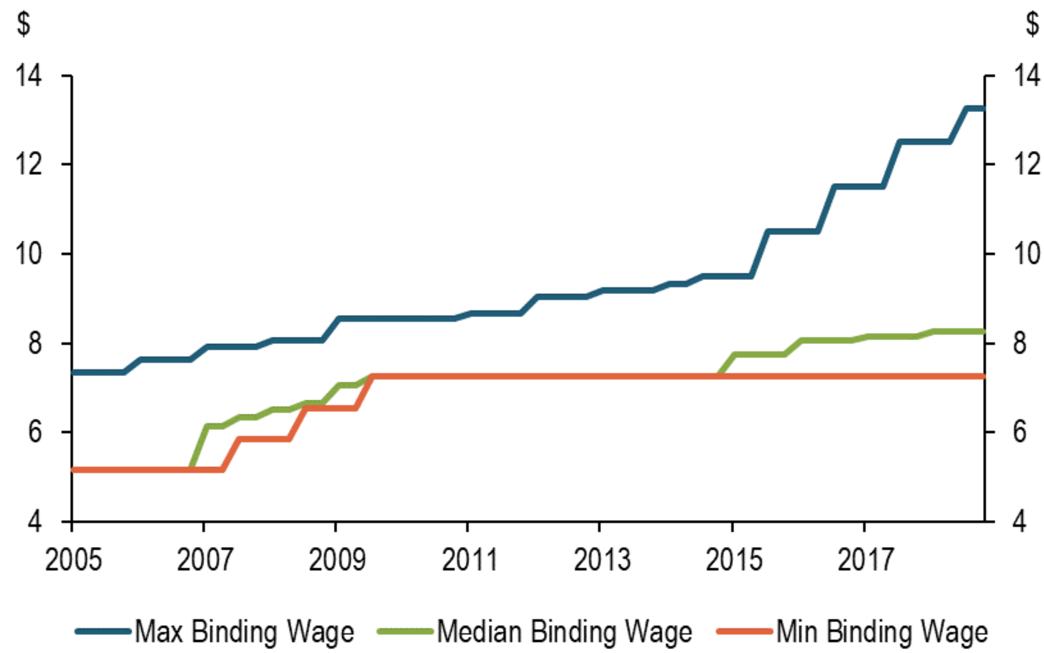

Figure 2: The range of state-level minimum wages. Minimum binding wage is the effective federal minimum wage.

our data fit this pattern (Figure 3). We believe that this underlying variation in the binding minimum wage across the U.S. states and the variation in the magnitude of the changes provide us with a great opportunity to identify the effects of the minimum wage hikes.

3.3 At-Risk Occupations and Additional Variables

Our identification scheme relies heavily on the assumption that some occupations are more exposed to minimum wage increases since the wage distribution can be more skewed to the left. As the size of employment around the minimum wage increases, more workers will be affected by the proposed minimum wage increase. In order to implement this identification strategy, we need to analyze hourly wage distribution by 2-digit occupations. We accomplish this by using the data from the Current Population Survey (CPS). More specifically, we focus on working individuals of age 16 and older, and exclude those who are self-employed or working without pay, from the fourth and the eighth month in sample, for which there is information about wages. We compute hourly wage data directly by using the hourly wage

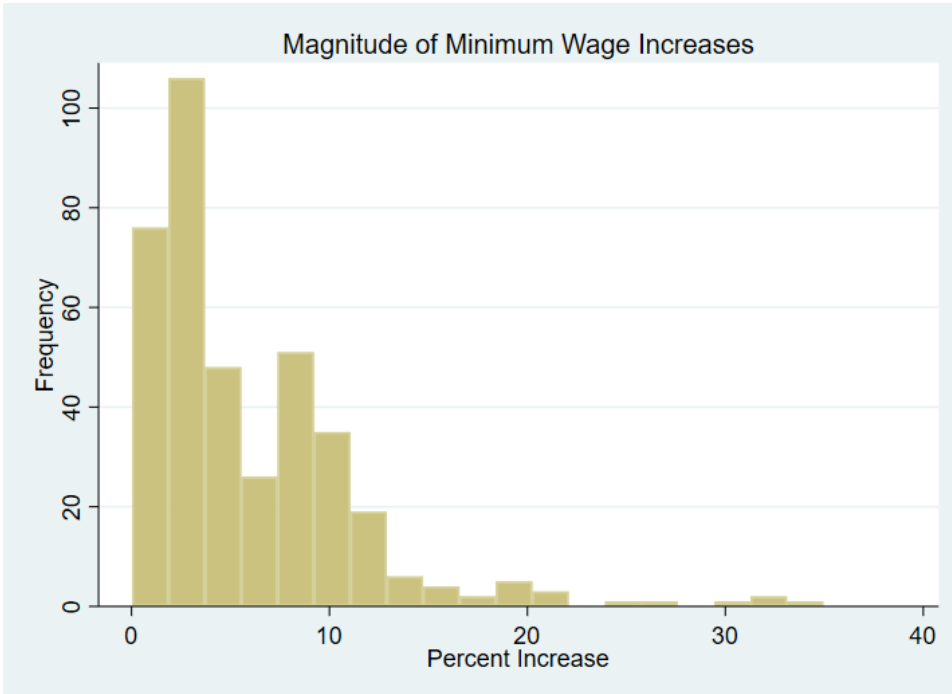

Figure 3: Distribution of minimum wage changes

measure in the CPS data. When that is not available, we rely on weekly hours worked and weekly wage data to compute an hourly wage.

Once we have data on hourly wage at the individual level, we can analyze wage distributions by occupation at the state level. Combining this information with the data on state-level binding minimum wage helps us gauge to what extent a particular occupation might be affected by the minimum wage increase. In order to quantify the size of the at-risk pool, first, we adapt a threshold rule of 10 percent relative to the minimum wage. In other words, we consider an occupation to be in the at-risk group, if the fraction of employment at or below 110 percent of the prevailing minimum wage is large enough. This is partly informed by the distribution of the minimum wage increases in the sample (Figure 3). Second, in order to pin down the relevant metric for the size of the at-risk pool, we adapt another threshold of 5 percent. Specifically, we designate an occupation to be in the at-risk group if at least 5 percent of the employment share for the occupation earns an hourly wage at or below the 110 percent of the prevailing minimum wage. We assess whether our results are robust to variations on these two threshold levels.

This methodology leads us to pick six different occupations as at-risk occupations for minimum wage changes. The 5 percent threshold follows naturally from the wage distributions. As Table 2 shows, there is a clear clustering separated by a 5-percent employment share. Table presents employment shares of workers in occupations (averaged across states) for a given year who earn at or below 110 percent of the prevailing minimum wage. The average share for the whole sample is about 4.5 percent, whereas the median share stands at 2.8 percent. We find the resulting classification reasonable and intuitive. Most of the occupations in the at-risk group are low-wage service sector jobs. Food processing and servicing related occupations have the largest share in the at-risk pool, on average about 21 percent, followed by sales related occupations at 14.2 percent, and office and administrative support occupations by 7.9 percent. Despite some variation over the years in terms of employment shares, the 5-percent rule is remarkably robust over time.

In some of our regressions, we control for additional location-specific variables. Specifically, we use log of the state or county-level population, employment or unemployment rate. When needed, these data from Local Area Unemployment Statistics (LAUS) program are pulled from HAVER Analytics.

Table 2: FRACTION OF AT-RISK EMPLOYMENT BY OCCUPATION

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	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	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	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	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	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	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	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 practitioner	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	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	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	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	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	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	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	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	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	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	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

Note: This table presents the average fraction of employment at or below 110 percent of the effective minimum wage. Effective level will correspond to the geographical location of the household in the CPS. For every year, we have averaged the fraction of employment across states and four quarters.

4 Empirical Approach and Results

In this section we describe our identification strategy in detail and present our empirical results.

4.1 Identification strategy

Our preferred empirical setup is essentially a triple-difference regression approach. We capture the effect of the minimum wage increases on vacancy creation by the following panel regression:

$$\log(V_{i,o,t}) = \alpha_{i,o} + \mu_{o,t} + \gamma_{i,t} + \beta \log(MW_{i,t}) * AtRisk_{i,o} + \varepsilon_{i,o,t} \tag{1}$$

In specification (1), the outcome variable that we are interested in is the log of (the number of) vacancies in county i, occupation o, and at time t. Variable $At\ Risk_{i,o}$ is an indicator function identifying whether occupation o in location i is one of the occupations with a large employment share due to workers earning at or below 110 percent of the prevailing minimum wage.[6] The parameter of interest is β and $\alpha_{i,o}$ is a county-occupation fixed effect, $\gamma_{i,t}$ is a county-time fixed effect (measured quarterly), and $\mu_{o,t}$ is an occupation-time fixed effect.

The coefficient of interest, β, is identified from the growth in vacancies for at-risk occupations relative to others around the time when minimum wage changes in that state and relative to the growth in national vacancies in the at-risk occupations. The power of the identification comes from the ability to control for arbitrary county specific trends in posted vacancies in the form of county-by-time fixed effects, $\gamma_{i,t}$. Note that, in contrast, a typical empirical approach in the minimum wage literature is to identify a narrowly defined group, such as teenage employment, or restaurant workers, and run the following regression:

$$\log(E_{i,t}) = \alpha_i + \gamma_{,t} + \beta \log(MW_{i,t}) + \varepsilon_{i,t}, \tag{2}$$

[6] Note that in our baseline specifications we assume this variable, $At\ Risk_{i,o}$ is independent of i.

where $E_{i,t}$ stands for employment in location i and at time t. We prefer our specification in equation (1) over this approach for several reasons. First, our preferred approach controls for occupation- and county-specific trends in vacancies within a specific location, as well as the unobserved variation in occupational-demand across locations. Second, we think our specification is equivalent to effectively running a placebo test. There are occupations in which only a small fraction of workers is employed at wage levels that are close to a prevailing minimum wage. Legal occupations, for instance, is one such example. We find that only 1.3 percent of the occupation earns at or below 110 percent of the prevailing minimum wage throughout our sample. Hence, by effectively comparing the effects of the minimum wage increase on at-risk occupations relative to those such as legal occupations, our empirical design provides us with a better identification of the causal effect.

Like most of the empirical literature, we focus on the short-term effects of minimum wage increases. However, due to the nature of the variable of interest (vacancies), and the timing of the announcement of minimum wage legislation both at the federal and state-level, we expect that there might be some forward-looking response in firms' vacancy postings. In order to analyze this potential effect, we also run an empirical specification, where we introduce dynamic leads and lags of the change in the effective minimum wage into equation (1).

Finally, following the influential work by Dube et al. (2010), we also implement a contagious-county specification of our main identification strategy. The main idea here 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 exogenously 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 running the following regression:

$$V_{i,o,p,t} = \alpha_{i,o} + \gamma_{o,p,t} + \beta \log(MW_{i,t}) * AtRisk_{i,o} + \varepsilon_{i,o,p,t}. \quad (3)$$

where p stands for a county-pair. However, we can still include very granular fixed effects for local labor market conditions by estimating the effect of minimum wage increases using only contiguous counties along the state borders, which allows us to include a county-pair-by-time-by-occupation fixed effect.

4.2 Results

Baseline Estimates

We estimate our preferred specification in equation (1) with the panel data we constructed using HWOL and the minimum wage data we compiled building on Vaghul and Zipperer (2016). In this specification, the unit of observation is an occupation in a county in a particular quarter. Table 3 reports our baseline estimation results. The first three columns report the estimated impact of minimum wage increases on total vacancies (i.e. the stock) and the remaining columns report the estimated coefficients for the impact on new job openings (vacancies less than 30-days old).

As column (1) in the Table 3 shows, we find a negative and statistically significant effect of minimum wage increases on vacancies. The estimated elasticity of vacancies for at-risk occupations are economically meaningful as well: β = -0.24. In other words, a 10 percent minimum wage increase reduces vacancies by about 2.4 percent for the occupations that employ more workers who are in the at-risk pool. To provide some context for this magnitude, consider the aggregate decline in vacancies by different occupations during the Great Recession. The average decline in 2-digit occupations was 20 percent during the recession.[7] Considering that the Great Recession was one of the largest economic shocks

[7] From December 2007 to July 2019.

Table 3: IMPACT OF MINIMUM WAGE ON STOCK AND FLOW OF VACANCIES

	log (Vacancies)			log (New Vacancies)		
Dependent Variable	(1)	(2)	(3)	(4)	(5)	(6)
log(MW_{t-2})*At-Risk			0.060			0.066
			(0.127)			(0.140)
log(MW_{t-1})*At-Risk		0.063	0.100		-0.001	0.009
		(0.104)	(0.071)		(0.090)	(0.085)
log(MW_{t})*At-Risk	-0.241***	0.011	-0.060	-0.215**	0.031	-0.027
	(0.083)	(0.086)	(0.066)	(0.080)	(0.083)	(0.067)
log(MW_{t+1})*At-Risk		-0.355***	-0.076		-0.291***	-0.068
		(0.109)	(0.066)		(0.096)	(0.079)
log(MW_{t+2})*At-Risk			-0.322**			-0.260*
			(0.125)			(0.132)
Fixed Effects						
County x Time	Yes	Yes	Yes	Yes	Yes	Yes
County x Occupation	Yes	Yes	Yes	Yes	Yes	Yes
Occupation x Time	Yes	Yes	Yes	Yes	Yes	Yes
Clusters	51	51	51	51	51	51
Observations	2,930,908	2,834,751	2,729,919	2,752,397	2,668,600	2,570,188
R-squared	0.921	0.922	0.922	0.928	0.929	0.930

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: This table reports OLS regressions for the dependent variable log(vacancies) for each occupation o, in county c at time t (quarterly). Columns (1) - (3) display results for the stock of vacancies and the remaining columns report the regressions results for new job openings (vacancies that has been posted within the past 30 days). Standard errors are clustered by state that ever hit the U.S. economy, a decline of 2.4 percent in response to a 10 percent increase in minimum wage is very significant.

It is natural to think that vacancy posting behavior by firms have some forward-looking element. In the context of frictional labor markets, where filling a vacancy takes time and resources, vacancies respond to shocks first, relative to other equilibrium variables such as unemployment or employment (Mortensen and Pissarides, 1994; Pissarides, 2000). On the other hand, most minimum wage increases are anticipated and often legislative debate at the state level can precede the actual implementation by a few quarters.[8] Hence, we would like to explore if this negative impact of minimum wage increase is led by a preemptive adjustment by the firms before the minimum wage change is enforced. We add dynamic leads and lags to our baseline specification in column (1).

Column (2) of Table 3 shows that when we add one lag and one lead of the minimum wage interaction term, the contemporaneous effect declines substantially and becomes insignificant. This, however, is more than offset by the response of vacancies (today) to a minimum wage increase in the next quarter. The coefficient further declines to -0.36, indicating a much larger elasticity for vacancies to a proposed minimum wage increase one quarter ahead. The cumulative effect is still significant and around -0.28. Column (3) in Table 3 extends this to a larger window around the minimum wage change and confirms our expectation that most of the negative effects are induced in advance. Extending this dynamic-lag structure beyond a two-quarter window runs the risk of confounding the lagged-effects of minimum wage changes with the anticipatory effects induced by frequent minimum wage changes that fall within a four-quarter window. Such frequent minimum wage changes are present in our sample.

The rest of Table 3 also confirms that minimum wage increases are associated with significant declines in new job openings for the at-risk occupations. The magnitudes for new

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

vacancies are not very different from the estimated magnitudes for total vacancies, ranging between -0.22 to -0.29. For the rest of the analysis we keep our focus on total vacancies.

Standard Diff-in-Diff Estimates

In our opinion, our preferred specification spelled out in equation (1) and presented above has many advantages. We can essentially use a lot of variation in the occupation composition of vacancy postings and each occupation's level of exposure to minimum wage increases in a nested model where we can then introduce many granular fixed effects to control for other arbitrary unobserved variation that has nothing to do with minimum wage changes. Here, we would like to evaluate, to what extent being able to have these granular fixed effects in the regression matters for our results. To do so, we estimate specification (2) separately with at-risk occupations and others by aggregating the level of vacancies in each group. In this exercise, the outcome variable is the level of vacancies in a county in quarter t, for a group of occupations. Since we do not have the flexibility of our preferred specification, we can only control for time invariant county-specific factors (α_i) and aggregate time varying trends ($\gamma_{,t}$).

Table 4 presents our results from this exercise. As column (1) highlights, we find basically no effect from a minimum wage increase for total vacancies in the group of at-risk occupations if we follow a typical Diff-in-Diff approach. We contend that this has a lot to do with the fact that we do not control for the time-varying unobserved variation at the county-level that is ignored due to lack of county-by-time fixed effects. To see this point, we add a county-level control variable, the unemployment rate, to the right hand-side. In principle, the coefficient estimate for this control essentially gives us the Beveridge curve relationship at the local level. That is, over the long-run, unemployment and vacancies are negatively correlated, which is corroborated by an estimate of -0.039 in column (2). If we control for the past history of the labor market, the coefficient estimate gradually turns negative and approaches the baseline estimates in Table 3.

Table 4: IMPACT OF MINIMUM WAGE ON VACANCIES – DIFF-IN-DIFF SPECIFICATION

	Total Vacancies in At-Risk Occupations					Total Vacancies in Other Occupations				
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\log(MW_t)$	-0.002	0.005	-0.115	-0.214	-0.323	0.417***	0.421***	0.388**	0.361	0.300
	(0.192)	(0.188)	(0.194)	(0.235)	(0.269)	(0.149)	(0.147)	(0.168)	(0.217)	(0.246)
Unemployment Rate_t		-0.039***					-0.027***			
		(0.006)					(0.005)			
Unemployment Rate_{t-4}			-0.029***					-0.020***		
			(0.005)					(0.005)		
Unemployment Rate_{t-8}				-0.019***					-0.016***	
				(0.004)					(0.005)	
Unemployment Rate_{t-12}					-0.009*					-0.013**
					(0.005)					(0.005)
Fixed Effects										
County	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clusters	51	51	51	51	51	51	51	51	51	51
Observations	168,196	168,104	156,274	144,171	132,324	170,865	170,773	158,505	146,194	133,867
R-squared	0.946	0.947	0.951	0.953	0.958	0.951	0.952	0.954	0.956	0.959

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Note: This table reports OLS regressions for the dependent variable log(vacancies)for at-risk occupations and the others separately following the specification in equation (2) in the text. Standard errors are clustered by state, and fixed effects are for county and time only.

A similar story emerges from columns (6) through (10). In the absence of any controls, total vacancies in occupations that do not employ many workers near the minimum wage threshold increase with a higher minimum wage, with a statistically significant and large elasticity estimate of 0.42. As the rest of the table implies this spurious correlation is mostly due to the fact that we are not controlling for county and occupation specific trends in the local labor market. Since nominal minimum wage is monotonically increasing for every location in our sample and there is a general upward trend in vacancies. Therefore, ignoring the underlying local trends could easily yield a positive effect. This exercise highlights the important methodological issue we raise in this paper. When the granular local effects are ignored, our estimation results seem to be biased towards zero for the impact of minimum wage increasess on vacancies. Conceptually, this bias might easily be present in the empirical work focusing on employment effects of minimum wage changes.

Adjacent Border-County Sample

In an influential study, Dube et al. (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. The assumption is that the unobserved heterogeneity between adjacent border-counties will be less pronounced than the average county in each state. They also present this as a general approach to incorporate multiple individual case-studies that had dominated part of the minimum wage literature at the time (Card and Krueger, 1994, 2000). Motivated by these arguments, we estimate the effects of minimum wage changes on vacancies using a similar border-county sample.

Table 5 presents our estimation results from this specification and shows that the estimated coefficient from this sample is almost identical to our baseline specification, with an estimate of β = -0.25. Adding leads and lags of interaction terms change the coefficient slightly, but overall conclusions from our baseline specification are confirmed in this sample as well. Our estimated negative effect of minimum wage increases on vacancies seem to be quite robust to this different empirical design.

Table 5: IMPACT OF MINIMUM WAGE ON VACANCIES - ADJACENT BORDER COUNTY SAMPLE

	log (Vacancies)		
Dependent Variable	(1)	(2)	(3)
$\log(MW_{t-2})$*At-Risk			-0.035
			(0.118)
$\log(MW_{t-1})$*At-Risk		-0.158	-0.056
		(0.116)	(0.101)
$\log(MW_{t})$*At-Risk	-0.246**	0.031	-0.032
	(0.117)	(0.108)	(0.106)
$\log(MW_{t+1})$*At-Risk		-0.172	0.085
		(0.127)	(0.084)
$\log(MW_{t+2})$*At-Risk			-0.289**
			(0.132)
Fixed Effects			
County x Time	Yes	Yes	Yes
County x Occupation	Yes	Yes	Yes
Pair x Occupation x Time	Yes	Yes	Yes
Clusters	218	218	218
Observations	1,948,098	1,887,506	1,817,610
R-squared	0.965	0.965	0.966

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: This table reports OLS regressions for the dependent variable log(vacancies) for each occupation o, in county c of county-pair, p, at time t (quarterly). Standard errors are clustered by state-borders

4.3 Heterogenous Effects of Minimum Wage Increases

Heterogeneous Effects across Occupations

Our empirical approach did not discriminate between different occupations within the at-risk group. This might be misleading if the task content of an occupation matters for firms in 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 our data reveal on this question by focusing on detailed 2-digit occupations based on their classification.

The routine vs. non-routine distinction, and a further classification into routine manual, routine cognitive, non-routine manual and non-routine cognitive categories follow Jaimovich and Siu (2012) and Tüzemen and Willis (2013). From our list of at-risk occupations; food processing and servicing related occupations (SOC-35), building and grounds cleaning and maintenance occupations (SOC-37), personal care and service occupations (SOC-39) are considered non-routine manual occupations. Sales and related occupations (SOC-41), and office and administrative support occupations (SOC-43) constitute the routine cognitive group. The only occupation in the at-risk group in the routine manual category is transportation and material moving occupations (SOC-53). There is no occupation in the non-routine cognitive group.

Table 6 replicates the baseline regression result in column (1) for convenience along with new results exploring the finer classifications for the task content of the occupations. Column (2) confirms the negative and statistically significant effects of the minimum wage changes on vacancies. This negative effect does not seem to be led by the routine occupations in the at-risk group. Column (3) refines this dimension further and reveals that manual occupations, not necessarily routine ones, are negatively impacted by the minimum wage changes.

Table 6: IMPACT OF MINIMUM WAGE ON ROUTINE JOBS

	log (Vacancies)			log (New Vacancies)		
Dependent Variable	(1)	(2)	(3)	(4)	(5)	(6)
log(MW$_t$)*At-Risk	-0.241***	-0.321***	0.037	-0.215**	-0.261**	0.008
	(0.083)	(0.133)	(0.093)	(0.080)	(0.134)	(0.083)
log(MW$_t$)*At-Risk*Routine		0.149			0.086	
		(0.139)			(0.128)	
log(MW$_t$)*At-Risk*Routine Manual			-0.632***			-0.557***
			(0.191)			(0.184)
log(MW$_t$)*At-Risk*Non-Routine Manual			-0.358***			-0.269***
			(0.156)			(0.145)
Fixed Effects						
County x Time	Yes	Yes	Yes	Yes	Yes	Yes
County x Occupation	Yes	Yes	Yes	Yes	Yes	Yes
Occupation x Time	Yes	Yes	Yes	Yes	Yes	Yes
Clusters	51	51	51	51	51	51
Observations	2,930,908	2,930,908	2,930,908	2,752,397	2,752,397	2,752,397
R-squared	0.921	0.921	0.921	0.928	0.928	0.928

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: This table reports OLS regressions for the dependent variable log(vacancies) for each occupation o, in county c at time t (quarterly). The interaction term Routine indicates whether the occupation is a routine one. RM, RC and NRM, refer to a slightly 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 (3) is the non-routine cognitive group (SOC-11 through SOC-29. Note that this group does not have any at-risk occupations.

5 Robustness

Our results clearly show that minimum age increases are associated with a large and significant decline in job openings for at-risk occupations. Our definition of at-risk occupation relied on two thresholds that we picked. Even though we think we have good arguments for the legitimacy of the thresholds, we want to analyze how robust our results are to these thresholds. We also examine how a particular measurement issue in the vacancy data affects our results.

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 a test for the robustness of our 5 percent threshold. Dropping building and grounds cleaning and maintenance occupations, for instance, effectively brings the threshold to 6.5 percent from 5.

Figure 4 presents point estimates and the 95 percent confidence intervals around them as we remove one occupation from the at-risk group at a time. None of these exclusions seem to be changing our baseline result at all. The lowest elasticity we get falls to -0.17 (when transportation is 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 basic definition of the at-risk occupation group.

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 correlation driven by these somewhat

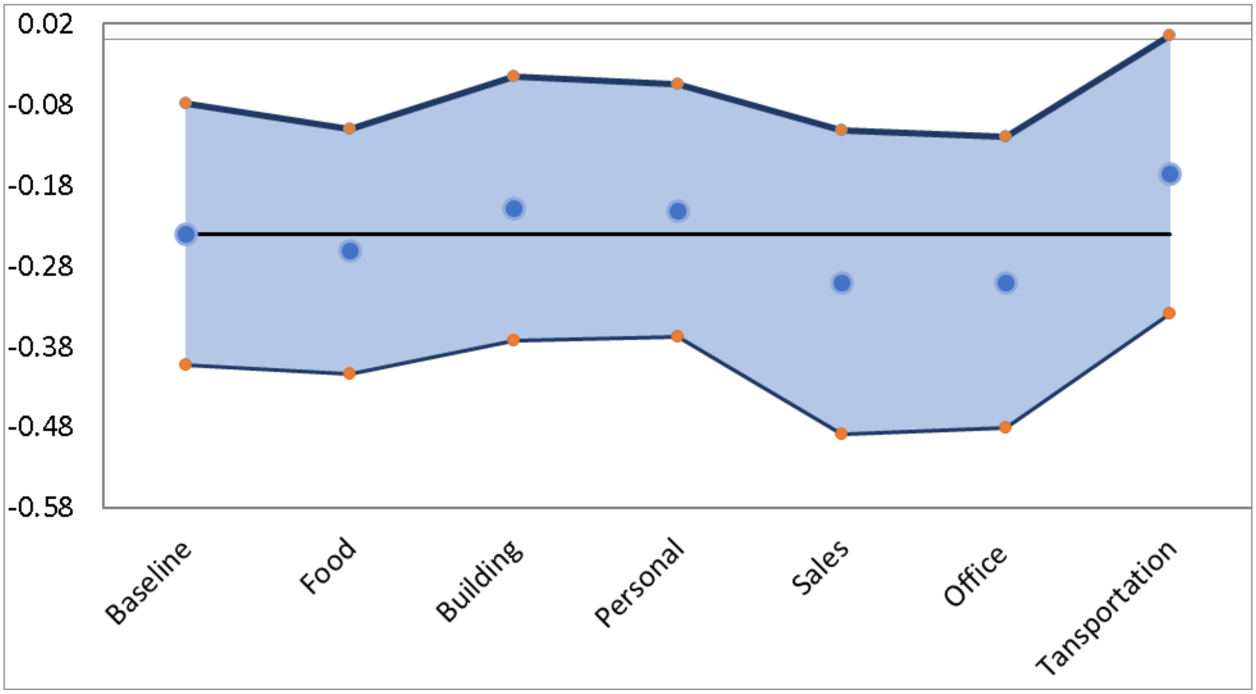

Figure 4: Estimates from baseline specification with at-risk occupations removed from sample one by one.

arbitrary changes. We can test how robust our results are for this measurement issue with two possible alternatives. We present these two alternatives along with the baseline result for convenience in Table 7.

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 one-million observations, quite a large increase relative to the baseline. However, it barely affects our baseline result, yielding a slightly lower elasticity of -0.25. Another transformation we consider is effectively renormalizing the zero observation by using $\log(V_{i,o,t}+1)$ for our outcome variable, instead of $\log(V_{i,o,t})$. This transformation also does not change the main conclusion, as the last column of Table 7 shows. We conclude that our results are robust to this particular measurement issue with the vacancy data as well as the definition of at-risk occupations.

Table 7: ROBUSTNESS - MEASUREMENT OF VACANCY DATA

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

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: This table reports OLS regressions for three different transformations of the dependent variable vacancies for each occupation o, in county c at time t (quarterly). The first column repeats the baseline result where we transform vacancy level with a simple logarithmic function. The second column use a transformation with inverse-hyperbolic sine function and the last column renormalizes the 'zero' observations by adding 1 before logarithmic transformation.

6 Conclusion

In this paper, we have proposed a novel identification strategy to estimate the impact of minimum wage increases on vacancies, a labor market variable that has not been studied in the large minimum wage literature. Our identification strategy builds on the idea that not all occupations will be similarly affected by minimum wage increases. There are occupations in which very few workers work at or near the prevailing minimum wage level. Intuitively, one should not expect to see any direct effects from a minimum wage increase in this case. We formalize this and identify six 2-digit occupations as potentially at-risk occupations. Our results point to statistically significant and large negative effects. Vacancies posted for occupations in the at-risk group face a 2.4 percent drop in response to a 10 percent rise in the prevailing minimum wage relative to other occupations. This baseline result seems to be driven by a strong preemptive response by the firms, cutting vacancies in advance of the minimum wage change. We find mixed evidence about the vulnerability of routine jobs to minimum wage increases. Instead, we find strong evidence that manual occupations among the at-risk group are behind the significant negative effect found in the baseline.

The literature on employment effect of minimum wage increases has been contentious, arguing for different empirical designs and delivering sometimes starkly different estimation results. 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 in our paper 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 provided us with similar estimation results.

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