Employment Costs of an Increasing Minimum Wage for Workers with Disabilities

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Abstract

Congress introduced legislation to increase the Federal minimum wage from $7.25 to $15 per hour over seven years in May, 2017 (S. 1242). This paper uses a structural unemployed labor market search model to simulate how such changes may differentially affect employment for workers with and without disabilities. Monthly data comes from the 2016 Current Population Survey, and disability is defined as self-reported functional limitations. Results simulating an increase in the Federal Minimum Wage from $7.25 an hour to $10, $12, and $15 suggest workers with disabilities could experience additional unemployment that is approximately four to five times larger than their counterparts. While this model simulation showcases the asymmetric employment costs of a rising minimum wage for workers with disabilities, it does not consider the benefits, which may also be disproportionately allocated to the same group. Nevertheless, it is an important aspect to consider, and future research should address benefits.

1 Introduction

As recently as May 2017 the U.S. Congress introduced legislation to increase the Federal minimum wage from \$7.25 per hour to \$15 over a seven year period (S. 1242). Low-wage workers who remain employed following a minimum raise increase experience higher hourly earnings, which can compress the earnings distribution (Autor, Manning, and Smith 2016; Bárány 2016; Neumark, Schweitzer, and Wascher 2004). However, traditional theory posits that such changes should be inversely related with employment, and various (though importantly, not all) empirical results corroborate elements of the theory (Gorry 2013; Meer and West 2015; Neumark, Schweitzer, and Wascher 2004; Card and Krueger 1994). The lowest part of the earnings distribution is thought to be most sensitive to changes in the minimum wage, and studies often focus on populations that are most sensitive to the minimum wage (Gorry 2013; Flinn 2011; Card and Krueger 1994).

On average, persons with disabilities tend to experience lower educational attainment, earnings, income, employment, and a higher incidence of poverty (Lauer and Houtenville 2017; Ryan and Bauman 2016; Brucker et al. 2015; Meyer and Mok 2013; Burkhauser and Stapleton 2004). These documented economic disadvantages should present a high level of sensitivity to changes in minimum wage policy. Additionally, this population represents a sizable minority of the overall U.S. population, with approximately one in eight civilians living in the community as of 2015 reporting a functional (seeing, hearing, cognitive, ambulatory, self-care, or independent living) limitation (Lauer and Houtenville 2017). The Social Security Administration also estimates that one in four U.S. adults entering the labor force will experience a disability at some point during his or her working-age career (SSA 2017), and survey-based research puts this probability significantly higher, over 50%, including more temporary bouts of disability (Meyer and Mok 2013; Laditka and Laditka 2017).

Technically persons with disabilities can legally be paid a wage that is below minimum wage (Bradley 2017; GAO 2001), but proposed legislation would eventually remove that exemption (S. 1242). It is unclear from existing research how the proposed legislation might quantitatively affect labor outcomes for persons with disabilities. This paper is a first attempt to address this knowledge gap and provides an estimate of potential employment costs from a supply-side perspective of increasing the minimum wage. It structurally estimates the unemployed labor market search process for persons with and without disabilities using monthly data from the 2016 U.S. Current Population Survey (CPS). Using the model's estimated parameters, simulations setting minimum wages to \$10, \$12, and \$15 an hour project the partial equilibrium response of labor. In this framework, the model can only predict increased unemployment, so the important contribution will be the relative responses of the two populations (those with and without disabilities). It is expected that workers with disabilities will experience lower contact rates, higher rates of exogenous termination, and less disutility of unemployment. Minimum wages are expected to disproportionately affect persons with disabilities given their observed existing disadvantages. As a preview of the results in this study, workers with disabilities bear approximately four to five times the employment response burden relative to persons without disabilities for each of the simulated increases in minimum wage. However, it is imperative to note that these estimates focus only on *costs* of the minimum wage, yet persons with disabilities are also likely to experience relatively higher benefits when applicable.

The rest of this paper is organized into four additional sections and an appendix. Section two gives some background to contextualize the question at hand. Section three discusses the data and modeling techniques. Section four presents results, including the minimum wage simulation, and section five discusses limitations and future research. The Appendix (section A1) contains additional details including demographic information of the sample, and some key mathematical derivations of the value fuction and maximum likelihood estimation. The model is from Flinn (2011), specifically the continuous search model with bargaining and a binding minimum wage, and the full derivation of that model is explained in detail in that text.

2 Background

Studies consistently show that persons with disabilities typically encounter adverse labor market outcomes and lower educational attainment. Employment rates among persons with disabilities are relatively low. For example, in 2016 the employment rate for persons with disabilities was 34.9% relative to 76% in the population without disabilities (Lauer and Houtenville 2017). The literature has also identified a protracted decrease in employment among the population (Kraus and Houtenville 2018; Houtenville and Lauer 2014; Burkhauser and Stapleton 2004). There is significant heterogeneity in employment outcomes based on specific conditions, and although persons with hearing or vision limitations tend to be relatively less disadvantaged, they still experience much lower employment rates (51% and 42% respectively) (Lauer and Houtenville 2017). Earnings are also estimated to be much lower for persons with disability years after onset, but also depending on the type of condition. For example, Meyer and Mok (2013) estimate that ten years after disability onset, earnings are approximately 79% lower for those experiencing a chronic and severe work-limiting disability, while earnings drop approximately 9% three years after onset for those with a temporary condition (Meyer and Mok 2013).

Some potential correlates of adverse labor market outcomes include lower educational attainment, higher job-loss, lower wage offers, and decreased social capital. Approximately 60% of the U.S. population without disabilities attended some college, while that figure is around 40% for persons with disabilities (Ryan and Bauman 2016, Table 1). Furthermore, such differences can emerge at early ages for youth with disabilities (Mann and Wittenburg 2015). Among job-seekers, wage-offers are on average lower for persons with disabilities (Mann and Wittenburg 2015). Some research also suggests there may be additional constraints on labor search for these individuals through decreased access to social capital (Langford, Lengnick-Hall, and Kulkarni 2013). Once employed, job loss also presents a higher risk (Mitra and Kruse 2016), making the labor market particularly turbulent for persons with disabilities.

Programs and policies, such as Social Security Disability Insurance (SSDI), Supplemental Security Insurance (SSI), and the Americans with Disabilities Act (ADA), aim to alleviate some disadvantages associated with labor market participation and disability. However, some research suggests there could be unintended consequences to the legislation. SSDI/SSI could incentivize workers with disabilities to leave the labor force completely, and may not provide enough incentives for firms to make minor accommodations that could otherwise enable individuals with less severe limitations to remain in the labor force (Autor 2011). While such incentives could produce an observed declining employment rate for persons with disabilities (Burkhauser and Stapleton 2004), another hypothesis is that the ADA could have made contributions to falling employment (Acemoglu and Angrist 2001). In a similar way, minimum wage policy could adversely affect employment. However, as with all these programs and policies, that focuses only on the cost side of welfare.

Persons with disabilities have a unique relationship with the minimum wage under current law. These individuals are part of an exemption in the Fair Labor Standards Act, (i.e. the minimum wage policy), under the 14(c) Subminimum Wage Certificate Program. Unlike other subminimum wage earners (e.g. restaurant workers receiving tips), there is no minimum wage. Workers can be paid a "productivity adjusted" wage (DOL 2012; Bradley 2017), and in some cases, legal wages have been reported to be less than a dollar an hour (GAO 2001). While this certificate program is technically available, the application of the practice appears to be less widespread. The Government Accountability Office reported in 2001 that the best participation estimates were 424,000 workers in 5,600 establishments; however, the same report also noted the Department of Labor did not keep accurate data (GAO 2001). If these numbers are loosely accurate to today's population, then participation in the subminimum wage program would amount to approximately 2% of working-age persons with disabilities, or 5.7% of employed persons with disabilities[1]. At the time of the report, the vast majority (95%) of individuals paid a subminimum wage under this exemption were employed at a "work center," which often provide other services such as transportation, counseling, and in some cases housing (GAO 2001). From the data collected for the present study, there is little evidence of subminimum wage reports[2].

Minimum wages are, and likely will continue to be, a controversial policy debate. One aspect that is somewhat less contentious is that impacts are most acutely felt near the bottom of the distribution (Autor, Manning, and Smith 2016; Neumark, Schweitzer, and Wascher 2004). On the benefit side, empirical evidence suggests there is a positive wage elasticity (Dube, Lester, and Reich 2016; Neumark, Schweitzer, and Wascher 2004). Higher wages then can translate into earnings distribution compression (Bárány 2016; Autor, Manning, and Smith 2016), although these two studies disagree on the extent to which there may be spillovers above the minimum wage binding point in the distribution. One key aspect to keep in mind when considering these benefits is that the inequality reduction and earnings compression occurs among those who remain employed.

[1] This is from population estimates in Lauer and Houtenville 2017 of approximately 20 million working age, and 7.4 million working age, employed persons with disabilities among the population living in the community.

[2] In the present study's population, there are 4 cases of self-reported sub-minimum wage offers in the population with functional limitations relative to 89 in the population without functional limitations, each representing about 0.2% of the respective population.

Basic economic theory unequivocally predicts an inverse relationship between minimum wages and employment. However, Card and Krueger (1994) provide evidence to suggest the basic theory may not adequately capture actual labor market experiences for low-wage workers. They found an increasing minimum wage in New Jersey relative to Pennsylvania had no evidence supporting decreased employment (Card and Krueger 1994). Neumark, Schweitzer, and Wascher (2004) however found an initial drop in employment among low-wage workers (that subsequently dissipates) followed by a reduction in hours using the Current Population Survey. Dube, Lester, and Reich (2016) suggests the employment elasticity is negative with respect to the minimum wage, but statistically indistinguishable from zero. Some research attempts to align the empirical evidence with traditional theory by suggesting there may be little to no initial employment effect, but the growth of employment could slow significantly over several years (Meer and West 2015). Dube, Lester, and Reich (2016) finds that while the stock of employment may be statistically unaffected by changes in the minimum wage, the flow of employment opportunities (quits, terminations, and turnover) is statistically significant and negative. Finally, age or experience seem to create heterogeneous experiences of labor market outcomes, specifically with young and inexperienced workers being most sensitive to changes in the policy that dissipate with age (Gorry 2013; Flinn 2011).

With legislative and public interest in debating current minimum wage policies, it is imperative to have a well-rounded understanding of the costs and benefits. While this paper currently addresses only the costs, it is an important empirical part of the puzzle. Given the protracted decline in employment for persons with disabilities (Burkhauser and Stapleton 2004), lower earnings (Meyer and Mok 2013), and proposals to eliminate the minimum wage exemption (S. 1242), estimated employment costs associated with raising the minimum wage specifically for persons with disabilities are needed to understand how opportunities may be affected.

3 Data and Methods

Data comes from the monthly Current Population Survey (CPS) for January 2016 through December 2016. Given the relatively low prevalence of persons with functional limitations in the labor force, data from the single year are pooled under the assumption that labor market conditions are relatively constant. Limiting the sample to a single calendar year prevents observing the same individual twice[3]. The key variables for the analysis are a self-reported disability status (binary), hourly earnings, and duration of current unemployment spell (if unemployed). The sample consists of adult civilians of working age (25-62) who are in the labor force and part of the outgoing sample (months 4 and 8) of CPS. Young labor market participants (age 19-24) are excluded because employment responses are likely more sensitive to changes in the minimum wages for this population (Gorry 2013; Flinn 2011). Self-employed individuals and those working without pay are excluded from the sample. Due to different minimum wages across the country, the sample is further restricted to only those states that utilize a binding Federal minimum wage of $7.25 per hour[4].

Disability is defined by functional (i.e. hearing, vision, cognitive, ambulatory, self-care, or independent living) limitations. If the respondent reports a limitation for any one of the possible six categories, he/she is classified as an individual reporting a disability. Table 1 presents the relative proportions of persons with disability (as defined in this study) in the 12-month pooled sample of U.S. individuals for states where the Federal minimum wage of $7.25 is binding. Although this study does not further disaggregate by specific limitation, for informative purposes it is useful to consider the partition of disability by type of limitation

[3]The sample only uses observations of the outgoing samples in months four and eight.

[4]These States include: Alabama, Georgia, Idaho, Indiana, Iowa, Kansas, Kentucky, Louisiana, Mississippi, New Hampshire, North Carolina, North Dakota, Oklahoma, Pennsylvania, South Carolina, Tennessee, Texas, Utah, Virginia, Wisconsin, and Wyoming

among the work force. Effects of disability are strongly heterogeneous based on impairment type[5], so it is helpful to understand the makeup of the population. Future research could attempt to disaggregate disability further to understand the gradients of disadvantage associated with certain limitations with a larger sample.

Table 1: Prevalence of specific limitation among persons with limitations

	Hearing	Seeing	Cognitive	Ambulatory	Self-care	Independent living
January	0.28	0.16	0.25	0.40	0.05	0.10
February	0.41	0.24	0.24	0.29	0.05	0.13
March	0.36	0.16	0.24	0.38	0.06	0.12
April	0.31	0.13	0.31	0.37	0.04	0.11
May	0.35	0.16	0.32	0.31	0.06	0.15
June	0.34	0.16	0.24	0.42	0.05	0.10
July	0.31	0.20	0.35	0.35	0.04	0.12
August	0.27	0.14	0.34	0.45	0.09	0.14
September	0.37	0.14	0.27	0.37	0.06	0.13
October	0.31	0.17	0.26	0.40	0.05	0.11
November	0.34	0.23	0.25	0.43	0.07	0.15
December	0.36	0.10	0.26	0.35	0.04	0.10
Total	0.33	0.17	0.28	0.38	0.06	0.12

As a percent of persons with limitations

Unemployed individuals are all those who report non-zero durations of employment search in the survey. Hourly wages are calculated using a hierarchy of preferred data. The preferred measure is self-reported hourly wages. If an individual does not report hourly wages, reported weekly earnings divided by reported usual hours worked per week are utilized as a replacement. In some cases, the "usual" hour report is that hours vary. In that case,

[5] See Kavanagh et al. (2015) or Meyer and Mok (2013)

reported actual hours worked last week are used if, and only if, it is in what might be a "reasonable" range[6]. Next, the sample is trimmed at the top and bottom 2% of the monthly sample regardless of disability status to account for outliers, while not removing too much data.

Each month there are approximately 9-29 observations that indicate employment, yet do not have a recorded hourly wage. There are also 102 total observations that report zero wages and zero weeks of unemployed search. Both of these categories are combined into "unreported wages". There is some indication that there may be a small selection bias present in unreported wages in that Whites (OR: 1.6), individuals with a Master's degree or higher (OR: 1.9), and people who are older than 55 (OR: 1.7) are more likely to have an unreported wage. Notably however, persons with disabilities are not more likely to have an unreported wage (OR: 1.08, p-value 0.79)[7]. Unreported wages represent anywhere from 0.34 to 0.88 of a percent in each monthly sample. Due to the small quantity and the fact that missing wages are not biased with respect to reported functional limitations, these observations are removed. A few remaining observations each month report a wage that is lower than the stated Federal minimum wage. While this could be accurate reporting of sub-minimum wages among the population with functional limitations, there are far more sub-minimal wage offers reported among persons *without* limitations[8]. Therefore, all these hourly wages are bumped up to $7.25, and the implicit assumption is that it is part of measurement or reporting error. Summary statistics of the sample are reported in Table 2, and conform to expectations of labor market disadvantage for persons with disabilities.

[6] This is certainly somewhat arbitrary; however, in the interest of preserving as much data as possible, any actual hour reports in the range of 20 to 70 hours are deemed "reasonable". Again, this measure is a last resort only if all other tiers of preferred hourly earnings are infeasible.

[7] Similar conclusions can be drawn when examining selection bias on missing wages and zero wages, zero search separately.

[8] There are 4 cases of sub-minimum wages in the sample from persons with disabilities relative to 89 cases for persons without disabilities.

Table 2: Mean observations in the sample

	Time Unemployed	Unemployment Rate	Wage
Non-limited	0.863	0.037	21.273
Limited	2.580	0.093	16.783
Total	0.929	0.040	21.102

Sample: civilians in the laborforce age 25-62

Time unemployed is in weeks

The analysis uses the continuous unemployed labor market search model with bargaining and a binding minimum wage from Flinn (2011). The Nash Bargaining parameter is set equal to $\frac{1}{2}$, although that is relaxed in sensitivity analysis. Within this context, each worker's value of unemployed search takes the following form:

$$\begin{aligned}&\rho V_u(m)_k = \\ &b_k + \frac{\lambda_k}{\rho + \eta_k}\left[(m - \rho V_u(m)_k)(G_k(\hat{\theta}) - G_k(m)) + \alpha \int_{\hat{\theta}} ((\theta_i - \rho V_u(m)_k) dG_k(\theta))\right]\end{aligned} \tag{1}$$

Where k is an agent's type: either an individual with or without a functional limitation, and i is a particular individual within the subset k. ρ is the discount factor, which is held constant across agent types (and is set equal to 0.005). $\rho V_u(m)_k$ is what the reservation wage would be without a binding minimum wage, b_k is the instantaneous value of unemployed search, λ_k is the contact rate for offers, while η_k is the rate of exogenous employment termination. m is the (binding) minimum wage, which is equal to \$7.25 for all agents, while θ_i is the individual's match value within a productivity distribution. The relationship between the match value and the observed wage is (Flinn 2011):

$$\theta_i = \frac{w_i - (1-\alpha)\rho V_u(m)_k}{\alpha} \tag{2}$$

α represents the Nash bargaining power parameter, and is initially assumed to be one half (Flinn 2011 pg. 158 and Flabbi 2010). w_i is the observed wage, which can be equal to the minimum wage (m). All match values above the critical match value ($\theta^* = m$) will generate employment, but only match values in excess of $\hat{\theta} = \frac{m-(1-\alpha)\rho V_u(m)_k}{\alpha}$ will generate a wage above the minimum wage. In all cases, $\rho V_u(m)_k$ is what the reservation wage would be in the absence of a binding minimum wage. Using Maximum Likelihood Estimation, the full log likelihood function for either agent would take the form of the following equation[9]:

$$\begin{aligned}\ln L =& N_k \ln \lambda_k - N_k \ln(\eta_k + \lambda_k \tilde{G}(m)_k) + N_{u,k} \ln \eta_k + N_{u,k} \ln \tilde{G}(m)_k - \lambda_k \tilde{G}(m)_k \sum_{i=u,k} t_i \\ & + N_{m,k} \ln \left(\tilde{G}(m)_k - \tilde{G}(\hat{\theta})_k \right) - N_{w>m,k} \ln \alpha + \sum_{i=e,w>m,k} \ln g \left(\frac{w_i - (1-\alpha)\rho V_U(m)_k}{\alpha} \right)_k \end{aligned} \tag{3}$$

Parameters in the structural labor market search model are estimated using (3) for each agent type independently. The key parameters estimated in this process include λ_k, η_k, $\rho V_u(m)_k$, as well as the log-normal match distribution parameters μ_k and σ_k (mean and standard deviation respectively). Estimated parameters are substituted into (1) to back out the instantaneous value of unemployment, b_k for each agent.

[9] Additional details are in the Appendix, for full model derivation, see Flinn (2011)

Persons with disabilities are on average older and tend to have spent less time in formal education. Both these underlying characteristics of the population could also influence productivity and labor market outcomes. In an attempt to parse out the impact of education and age, a propensity-score matched sample of persons without disabilities is selected mirroring the age and education characteristics of persons with disabilities[10]. The model is re-estimated for this particular sub-sample to glean some information about the impact education and age may have on the estimated labor market parameters and outcomes.

The minimum wage simulation uses the estimated parameters ($\hat{\eta}$, $\hat{\lambda}$, and $\tilde{G}(m)$) for specific samples (non-limited, matched sample of non-limited, and limited) to estimate the partial equilibrium employment effect of increasing the minimum wage from \$7.25 to \$10, \$12, and \$15 for all agent types. Modeled unemployment is calculated as:

$$p(U) = \frac{\hat{\eta}_k}{\hat{\eta}_k + \hat{\lambda}_k \tilde{G}(m)_k} \tag{4}$$

In simulating additional unemployment, the estimated rate of exogenous termination ($\hat{\eta}_k$), contact rate ($\hat{\lambda}_k$), and average productivity (parameters underlying the match distribution, $G(m)_k$) are unaltered for each agent type. For this simple counterfactual, it is only the truncation point of the match distribution that changes for the new minimum wage.

For all modeling, reported standard errors are obtained from the Hessian matrix, and the match distribution is assumed to be log-normal. Parameters are restricted to their respective domains in Maximum Likelihood Estimation (MLE) using exponential transformations. The implicit reservation wage is restricted to be less than the minimum wage by utilizing $\rho V_U(m)_k = m - \exp(\psi_k)$, where m is the minimum wage and ψ_k is the parameter estimate in MLE.

[10]Results from a logit regression of key demographic characteristics regressed on the binary functional limitations indicator (Table A1 in the Appendix) show persons who are younger and with higher education are statistically less likely to report limitations. Table A2 shows group mean summary statistics for the full sample without limitations, the propensity-score matched sample without limitations, and sample with limitations. The matched sample is a nearest neighbor match on education and age.

4 Results

While observations outside states with a $7.25 binding minimum wage are excluded from the sample, it is nevertheless useful to consider the unadjusted unemployment rate by functional limitations and minimum wage level. Figure 1 shows that while unemployment in the U.S. hovers around 4% for persons without functional limitations regardless of the minimum wage level[11], the same cannot be said for persons with functional limitations. With the exception of states just above the Federal minimum wage, which are perhaps less reliable[12], the lowest state-level unemployment rate for persons with disabilities is in states with a binding Federal minimum wage (9.3%). In states with a minimum wage above $8, but less than $10, unemployment among persons with disabilities is about 11%. In states with minimum wages $10 or more (California, Massachusetts, and the District of Columbia), unemployment among persons with disabilities is markedly higher at 15%.

Table 3 presents results of the structural labor market estimation. $\rho \hat{V_U}(m)$ is the implicit reservation wage. $\hat{\mu}$ is the estimated average for the log-normal distribution of productivity matches, and $\hat{\sigma}$ is the associated standard deviation of the match productivity distribution. b is the instantaneous disutility of unemployed search, and "E(wage)" is the expected wage over observed matches[13]. Columns (1) and (4) are the parameter estimates, columns (2) and (5) are the lower limits of the 95% confidence interval, and (3) and (6) are the upper bounds of that interval.

[11] Note that these estimates are only among individuals aged 25-62

[12] These cases are peculiar due to an extremely small sample from Maine, New Mexico, and Missouri. Only 12 observations in these states report disability and unemployment.

[13] The reported expected wages are given by $E(w) = \alpha E(\theta) + (1-\alpha)\rho V_U(m)$, where θ is the log-normally distributed match parameter according to the assumptions outlined above with $E(\theta) = exp(\hat{\mu} + \frac{1}{2}\hat{\sigma}^2)$, and $\rho \hat{V_U}(m)$ is what the reservation wage would be if there were no minimum wage.

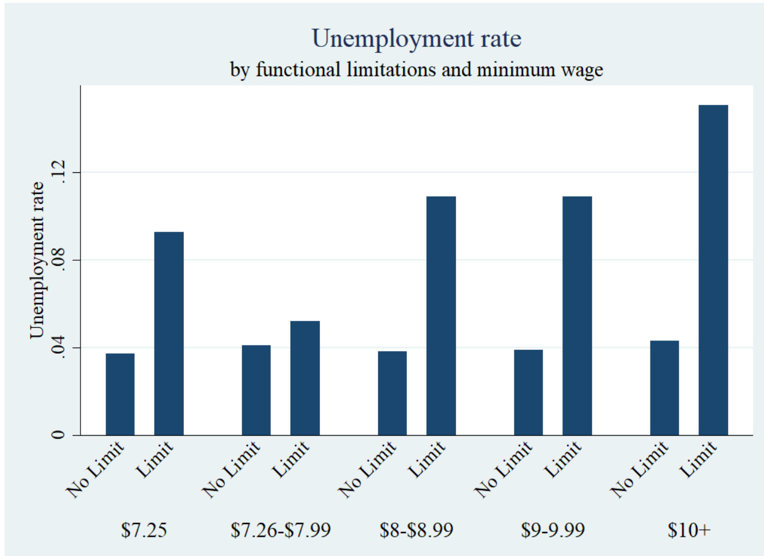

Figure 1: Gains in unemployment appear to be disproportionately allocated to persons with limitations as the minimum wage increases.

Persons with disabilities experience a lower contact rate ($\hat{\lambda}$) and about twice the estimated rate of exogenous employment termination ($\hat{\eta}$) in the labor market. Average match productivity ($\hat{\mu}$) for persons with disabilities tends to be lower, and expected wages are also substantially lower than their counterparts in the labor force who do no report any functional limitations. Instantaneous utility loss of unemployment (b) is more than double for the population without limitations relative to the population reporting some functional limitations. These differences could translate into a greater search incentive among the population without disabilities, and a lower reservation wage.

Demographic characteristics (educational attainment and age) of the population with disabilities appear to account for a small portion of the differences noted above. Table 4 shows results for the propensity-score matched sample of non-limited individuals relative to persons with limitations. In particular, the estimated contact rate of these two populations is similar, but the confidence interval on the matched sample is extremely large. While undoubtedly lower educational attainment and older ages have an effect on estimated pa-

	NL-est	NL-low	NL-high	L-est	L-low	L-high
$\hat{\lambda}$	0.04399	0.04205	0.04602	0.03770	0.03264	0.04355
$\hat{\eta}$	0.00169	0.00158	0.00180	0.00368	0.00299	0.00454
$\rho\hat{V_U}(m)$	6.49127	6.39051	6.58022	6.66067	6.32829	6.87318
$\hat{\mu}$	3.41364	3.40593	3.42135	3.14223	3.09854	3.18591
$\hat{\sigma}$	0.65089	0.64522	0.65656	0.68609	0.65325	0.71892
b	-95.69033			-42.59434		
E(wage)	22.01676			17.98025		

Table 3: Separate Estimation, Full sample, Minimum Wage Constraint

rameters, the full sample estimates are always contained within the 95% confidence interval of the matched sample of non-limited workers. Results still suggest persons with functional limitations retain labor market disadvantages, particularly higher termination rates, lower average productivity, and lower expected wages.

	NL-est	NL-low	NL-high	L-est	L-low	L-high
$\hat{\lambda}$	0.03964	0.03114	0.05046	0.03770	0.03264	0.04355
$\hat{\eta}$	0.00133	0.00094	0.00188	0.00368	0.00299	0.00454
$\rho\hat{V_U}(m)$	6.31333	5.55546	6.73225	6.66067	6.32829	6.87318
$\hat{\mu}$	3.40352	3.36309	3.44395	3.14223	3.09854	3.18591
$\hat{\sigma}$	0.63756	0.60837	0.66675	0.68609	0.65325	0.71892
b	-89.28461			-42.59434		
E(wage)	21.57992			17.98025		

Table 4: Sample of non-limited with similar demographic characteristics

Table 5 compares the models presented above with observations in the data. The model does an excellent job of matching the unemployment rate and the duration of unemployment in the data, but slightly underestimates expected wages, particularly for persons with disabilities (column 1 of Table 5).

Given the current policy environment, the minimum wage simulation is of key interest for this study. All estimated parameters are held constant ($\hat{\lambda}_k$, $\hat{\eta}_k$, $\hat{\mu}_k$ and $\hat{\sigma}_k$), and the only change is the value of the binding minimum wage. Under these circumstances, one can see that while unemployment expectedly increases in both populations, it does so much

	E(wage)	Unemployment Rate	E(time unemployed)	Hazard
Full sample (NL)	22.01676	0.03743	23.04956	0.04338
Matched Sample (NL)	21.57992	0.03291	25.55795	0.03913
Data (NL)	22.10064	0.03743	23.05770	
Full Sample (L)	17.98025	0.09283	27.78288	0.03599
Data (L)	18.50058	0.09286	27.78495	

Table 5: Minimum wage model comparison with data

more for the population with functional limitations. Mild increases in the minimum wage produce relatively mild employment effects; while larger increases are associated with a greater employment response especially among persons with disabilities. More specifically, in the case of a mild increase in minimum wage (to $10 an hour) the resulting increase in unemployment is less than 1% point for both populations. However, the resulting increase in unemployment for the population with limitations is approximately four to five times larger than the population without limitations in all situations, providing evidence of an asymmetric adverse employment effect for persons with limitations.

	Min. wage = 10	= 12	= 15
No Limitation	0.11	0.25	0.52
No Limitation, sample	0.10	0.21	0.46
Limitation	0.61	1.24	2.43

Table 6: Simulating additional unemployment with an increase in minimum wage

5 Discussion

The structural model for unemployed search reveals some rationale for higher unemployment among persons with disabilities. Typically individuals self-reporting functional limitations receive fewer offers for employment (lower contact rates) and nearly twice the probability of employment termination compared to the population without functional limitations. Using a propensity-score matched sample of persons without limitations, lower average levels of educational attainment and higher age are not likely the driving forces behind these results. If policymakers were to increase the minimum wage, the model simulation predicts that adverse employment responses would be disproportionately allocated to persons with disabilities.

Predictions of asymmetric employment consequences heavily concentrated among persons with disabilities is consistent with previous studies suggesting typically low-wage workers such as restaurant workers are often most sensitive to minimum wage changes (Dube, Lester, and Reich 2016; Neumark, Schweitzer, and Wascher 2004; Card and Krueger 1994). Because teens and young workers are known to experience high sensitivity to minimum wage changes (Dube, Lester, and Reich 2016; Gorry 2013; Flinn 2011), this study removes younger workers to only compare effects among workers aged 25-62. Additionally, lower educational attainment and advanced age could possibly impact a wage offer, yet the matched sample indicates that these characteristics do not contribute much to the observed results. Finally, these results are largely consistent with Figure 1, where we observe very little movement in overall unemployment among workers without limitations coupled with rather large increases in unemployment for persons with disabilities as the State's binding minimum wage increases. While this model simulates less than 1% additional unemployment for a $10 minimum wage, the unconditional average state-level unemployment from states with minimum wages between $8 and $10 represents about a 2% increase in unemployment. However, states with higher minimum wages likely have confounding characteristics and policies that may reinforce and/or interact with minimum wage policies.

There are a number of important model characteristics and limitations that warrant caution in applying specific estimates and results directly. First, the Nash bargaining parameter, α, is an exogenously defined parameter, characterizing the relative bargaining positions of the searcher and the firm for wage setting. While for simplicity, this analysis assumes the bargaining parameter equal to one half along the lines of previous research (Flinn 2011;

Flabbi 2010) for both subpopulations, it is reasonable to suspect there may be different relative bargaining positions. In table 7, the assumption of $\alpha = 0.5$ for all agents is relaxed, allowing $\alpha \in (0.25 : 0.75)$. Although there is some mild movement in parameters, including the estimated instantaneous value of unemployment, the unemployment rate is remarkably stable regardless of the value of α.

	λ_{NL}	η_{NL}	b_{NL}	U_{NL}	λ_L	η_L	b_L	U_L
$\alpha = 0.25$	0.043	0.002	-99.391	3.729	0.036	0.004	-42.982	9.287
$\alpha = 0.3$	0.044	0.002	-97.993	3.742	0.037	0.004	-42.710	9.280
$\alpha = 0.35$	0.044	0.002	-97.145	3.735	0.037	0.004	-42.551	9.293
$\alpha = 0.4$	0.044	0.002	-95.918	3.744	0.037	0.004	-42.453	9.290
$\alpha = 0.45$	0.044	0.002	-96.133	3.733	0.037	0.004	-42.497	9.285
$\alpha = 0.5$	0.044	0.002	-95.690	3.743	0.038	0.004	-42.594	9.283
$\alpha = 0.55$	0.044	0.002	-95.654	3.745	0.038	0.004	-42.747	9.288
$\alpha = 0.6$	0.044	0.002	-95.920	3.747	0.038	0.004	-42.987	9.282
$\alpha = 0.65$	0.044	0.002	-96.232	3.743	0.039	0.004	-43.192	9.307
$\alpha = 0.7$	0.044	0.002	-96.682	3.740	0.039	0.004	-43.870	9.274
$\alpha = 0.75$	0.045	0.002	-97.845	3.745	0.039	0.004	-44.559	9.283

Table 7: Robustness of alpha

Another reason for caution is that this model is in a partial equilibrium framework. There is no inclusion of capital in production, nor the firm's demand for labor. Therefore it is worth emphasizing again that the specific unemployment rates are less relevant than the comparison between the two groups. The interaction of disability with voluntary exit from the labor force is also present, and unaccounted for in this modeling. This exercise limits the sample to those who are in the labor force only, so it is unclear how persons with (and without) functional limitations may alter their labor market participation in the presence of an increasing minimum wage, even within a partial equilibrium framework. Additionally, the modeling assumes a relatively homogeneous group in estimation, while persons with disabilities in particular are known to experience heterogeneous outcomes (Kavanagh et al. 2015; Meyer and Mok 2013). Therefore, these results aggregate all persons with limitations in a way that likely obscures variations in employment responses. However, due to relatively low labor market participation among the population, it is necessary to aggregate individuals reporting any functional limitation, and even still results suffer from some imprecision. Finally, the minimum wage simulation also employs a relatively simple counterfactual that essentially re-truncates the match distribution at the new minimum wage, rendering those with match values less than the new minimum unemployed. Contact rates, termination rates, and the underlying distribution of wages all remain constant in the simulation.

A final major caveat to the results presented here is that the simulation only allows employment *costs*, and does not consider any policy benefits. Previous research has found inequality compression (Autor, Manning, and Smith 2016; Bárány 2016) and a positive wage elasticity among low-wage workers (Dube, Lester, and Reich 2016), which would likely also be applicable to persons with disabilities. While far from definitive, within this sample and framework there is some evidence of higher benefit incidence as well. For example, with an increase in the minimum wage to $15 an hour, approximately 18% of the population without disabilities would experience an average wage bump of $2.26. Conversely, 21% of the population with disabilities would experience an average wage bump of similar magnitude ($2.27).

In spite of these limitations, there are a number of strengths of the current project. Consistent with previous research, there appears to be some level of heterogeneous employment responses when facing a minimum wage increase that disproportionately affects workers near the bottom of the earnings distribution (Gorry 2013). It also corroborates findings of higher termination rates (Mitra and Kruse 2016) among persons with disabilities, and showcases employment disadvantages for persons with disabilities (Lauer and Houtenville 2017; Burkhauser and Stapleton 2004). Most importantly, this study allows simulating proposed policy legislation *prior* to implementation. Given the model's predictions, it is important to bear in mind the costs of increasing the minimum wage, especially among those who are already disadvantaged.

Future research stemming from this ongoing project should focus on incorporating some demand-side elements and possibly general equilibrium aspects to have more reliable estimates of predicted unemployment when facing an increase in the minimum wage. A more empirical approach with a triple difference model could explore state and time variations in addition to functional limitation status heterogeneity to create a retroactive analysis of previously observed minimum wage hikes. Given Figure 1 an empirical approach could corroborate the current results of disproportionate increases in unemployment among the population with functional limitations; however, finding an appropriate comparison in terms of geography, concentration of persons with disabilities, and corresponding policies, could be particularly challenging.

A1 Appendix

A1.1 Random Sample of Non-Limited Workers

Key demographic characteristics of workers with functional limitations differ on average relative to workers without limitations. A simple logistic regression (Table A1) shows workers reporting functional limitations in this sample are more likely to be older and have lower educational attainment. Demographic characteristics do not statistically differ by race or gender.

Table A1: Demographic Characteristics

	(1) Limited=1
Some College	0.0553
	(0.0605)
Associate's Degree	-0.246***
	(0.0746)
Bachelor's Degree	-0.601***
	(0.0681)
Advanced Degree	-0.713***
	(0.0905)
Female	-0.0402
	(0.0462)
White	-0.0785
	(0.0580)
Age	0.0365***
	(0.00219)
N	52467

Omitted categories: High School

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Nearest neighbor propensity scores are used to randomly select a sample of workers without limitations that mimic the demographic characteristics of workers with functional limitations. After selecting this subsample, mean demographic characteristics of the two samples are suitably similar as shown in table A2. Education and age are both categorical variables. For education the respective categories are: (1) a High School education, (2) Some college, but no degree, (3) an Associate's Degree, (4) a Bachelor's Degree, and (5) an Advanced Degree. Age categories are: (1) 25-34 years, (2) 35-54 years, and (4) 55+ years old.

Table A2: Group Mean Comparison

	No Limited	Sample Not Limited	Limited
Education	2.62	2.21	2.21
	(1.46)	(1.34)	(1.34)
Female	0.49	0.48	0.47
	(0.50)	(0.50)	(0.50)
White	0.81	0.82	0.80
	(0.39)	(0.39)	(0.40)
Age	42.66	46.91	46.91
	(10.75)	(11.02)	(11.02)
N	50464	2003	2003

(Standard errors)

A1.2 Solving the Model

The model used here is the standard unemployed labor market search model with a binding minimum wage, which can be found in Flinn (2011). The following highlights key steps of solving that model and its application to the present research question.

An agent's value of unemployed search problem is defined by the following value function (5), where $V_u(m)$ is the value of unemployed search in the presence of a minimum wage, and is equal to the discounted value of all possible events that can occur in a given (short) period of time (ε). An agent can receive an employment offer (λ), or not ($1-\lambda$). If an agent receives an offer, it can either be at the minimum wage ($\int_m^{\hat{\theta}}$) or above ($\int_{\hat{\theta}}$), in both cases the agent receives the value of employment (V_E). Alternatively, an offer may not be acceptable, in which case the agent receives a value of unemployment and continued search ($V_U(m)$). Employment matches are terminated at the rate of η, at which point the agent engages in employment search. Both employment matches and terminations follow a process that is memoryless, specifically the exponential distribution. In equation (5) the first term (b) is the instantaneous value of unemployed search. The second term is the value of receiving an offer that is not acceptable, and therefore the agent continues searching. The third is the value of receiving an offer equal to the minimum wage. The fourth is the value of receiving an offer above the minimum wage, and the fifth is the value of no offer and continued search. The final term accounts for any other events (or combinations) that can occur in a given period. As the time interval (ε) goes to zero, there are no event combinations that can occur.

$$\begin{aligned}&(1+\rho\varepsilon)V_U(m) = \\ &\quad b\varepsilon + \lambda\varepsilon \int_0^m V_U(m)dG(\theta) + \int_m^{\hat{\theta}} V_E(m)dG(\theta) + \int_{\hat{\theta}} V_E(m)dG(\theta) + (1-\lambda\varepsilon)V_U(m) + o(\varepsilon)\end{aligned} \tag{5}$$

Firms and job searchers bargain for the minimum wage according to a Cobb-Douglas process with bargaining parameter α. The value of employment simplifies to $\frac{w+\eta V_U(m)}{\rho+\eta}$, and therefore the quantity $(V_E(m) - V_U(m)) = \frac{w+\rho V_U(m)}{\rho+\eta}$. The value of an employment contract for a firm is: $\int_0^t (\theta - w)\exp(-\rho u)du$, and the expected duration of a contract follows an exponential distribution. Assuming the firm's outside option (not hiring and keeping the vacancy open) is zero, the final value to the firm of a match is: $\left(\frac{(\theta-w)}{\rho+\eta}\right)$. And within the bargaining framework, wages above the minimum wage will be: $w = \arg\max\,(V_E(m) - V_U(m))^{\alpha}\left(\frac{(\theta-w)}{\rho+\eta}\right)^{(1-\alpha)}$, or $w = \alpha\theta + (1-\alpha)\rho V_U(m)$. It should be noted that this will apply only to match values greater than some $\hat{\theta} = \frac{m-(1-\alpha)\rho V_U(m)}{\alpha}$. For all match values $\theta \in (m : \hat{\theta})$, the firm is willing to give up the requisite amount of their surplus to the job searcher in order to form a match as long as their value remains non-negative. Therefore, the critical match value is equivalent to the minimum wage: $\theta^* = m$, and all matches $\theta \in (m : \hat{\theta})$ are paid the minimum wage.

For the present paper, k represents two distinct populations: in this case: persons without functional limitations (NL) and persons with functional limitations (L). The minimum wage, discount factor (ρ), and bargaining parameter (α), are assumed to be the same for both populations. The latter assumption is later relaxed to allow for differing bargaining structures. ε is a small fraction of time that approaches zero in the limit: i.e. $\lim_{\varepsilon\to 0}\frac{o(\varepsilon)}{\varepsilon} = 0$. The reservation wage (what the wage would be in the absence of a binding minimum wage) is: $\rho V_U(m)_k$.

Given these assumptions, the value of unemployed search after simplifying is:

$$\rho V_u(m)_k = b + \frac{\lambda_k}{\rho+\eta_k}\left[(m - \rho V_u(m)_k)(G(\hat{\theta})_k - G(m)_k) + \alpha\int_{\hat{\theta}_k}(\theta - \rho V_u(m)_k)dG(\theta)_k\right] \quad (6)$$

Full details to finding the the maximum likelihood estimation can be found in Flinn (2011), Chapter 7. However, a few key steps are noted here. The model will estimate the following parameters: λ_k, η_k, $\rho V_U(m)_k$, and distributional $(G(\theta)_k)$ parameters, μ_k and σ_k. The populations (with and without functional limitations) are mutually exclusive, and separately estimated. Recall that both contact rates and rates of exogenous termination follow an exponential distribution. The hazard rate out of unemployment is the probability that a contact is made, and that the offer is acceptable, or $h_k = \lambda_k \tilde{G}(m)_k$, and the expected duration of unemployment is the inverse of the hazard, $E(t_u)_k = (\lambda_k \tilde{G}(m)_k)^{-1}$. Similarly, the expected time of employment is the inverse of the probability of termination, $E(t_e)_k = \eta_k^{-1}$. Therefore, the probability of observing an agent in the unemployed state is, $p(U)_k = \frac{\eta_k}{\eta_k + \lambda_k \tilde{G}(m)_k}$, and the probability of observing an agent that is employed is $p(E)_k = \frac{\lambda_k \tilde{G}(m)_k}{\eta_k + \lambda_k \tilde{G}(m)_k}$[14].

The probability of observing some length of unemployment is right-censored and subjected to the time-length bias. Under the assumption that the true duration is proportional to the observed duration and that time unemployed is exponential, the density is $f_U(t_u) = h_k(\exp^{-h_k t})$. Conditional on the employment state, employment at the minimum wage is given by $p(w = m|E) = \frac{\tilde{G}(m)_k - \tilde{G}(\frac{m-(1-\alpha)\rho V_U(m)}{\alpha})_k}{\tilde{G}(m)_k}$, which intuitively is the mass of the Cumulative Distribution Function between the bounds m, and $\hat{\theta}$, adjusted for the truncated distribution (we only observe employment if the match exceeds the critical match value, m). The probability of observing a wage above the minimum wage follows a similar construct: $p(w > m|E) = \frac{\tilde{G}(\frac{m-(1-\alpha)\rho V_U(m)}{\alpha})_k}{\tilde{G}(m)_k}$. Finally, the density of observed wages is $f(w|w > m, E) = \frac{\frac{1}{\alpha} g(\frac{w-(1-\alpha)\rho V_U(m)_k}{\alpha})}{\tilde{G}(\frac{m-(1-\alpha)\rho V_U(m)}{\alpha})_k}$.

[14]This is derived from knowing $p(U) = \frac{E(t_u)}{E(t_u)+E(t_e)}$, and $p(E) = 1 - p(U)$

After simplifying, the full likelihood takes the following form, where i represents the agent's employment state (unemployed or employed, and if employed, either at the minimum wage or above):

$$
\begin{aligned}
L = & \prod_{i=U} \frac{\eta_k h_k(\exp^{-h_k t_i})}{\eta_k + \lambda_k \tilde{G}(m)_k} \\
& \times \prod_{i=E,m} \frac{\lambda_k}{\eta_k + \lambda_k \tilde{G}(m)_k} \times \left(\tilde{G}(m)_k - \tilde{G}(\frac{m-(1-\alpha)\rho V_U(m)}{\alpha})_k \right) \\
& \times \prod_{i=E,w>m} \frac{\lambda_k}{\eta_k + \lambda_k \tilde{G}(m)_k} \times \frac{1}{\alpha} g \left(\frac{w-(1-\alpha)\rho V_U(m)}{\alpha} \right)_k
\end{aligned} \tag{7}
$$

And the log likelihood is:

$$
\begin{aligned}
\ln L = & N_k \ln \lambda_k - N_k \ln(\eta_k + \lambda_k \tilde{G}(m)_k) + N_{u,k} \ln \eta_k + N_{u,k} \ln \tilde{G}(m)_k - \lambda_k \tilde{G}(m)_k \sum_{i=u,k} t_i \\
& + N_{m,k} \ln \left(\tilde{G}(m)_k - \tilde{G}(\hat{\theta})_k \right) - N_{w>m,k} \ln \alpha + \sum_{i=e,w>m,k} \ln g \left(\frac{w_i - (1-\alpha)\rho V_U(m)_k}{\alpha} \right)_k
\end{aligned} \tag{8}
$$

References

Acemoglu, Daron and Joshua D Angrist (2001). "Consequences of employment protection? The case of the Americans with Disabilities Act". In: *Journal of Political Economy* 109.5, pp. 915–957.

Albrecht, James W and Bo Axell (1984). "An equilibrium model of search unemployment". In: *The Journal of Political Economy*, pp. 824–840.

Autor, David H (2011). *The unsustainable rise of the disability rolls in the United States: Causes, consequences, and policy options*. Tech. rep. National Bureau of Economic Research.

Autor David, H, Alan Manning, and Christopher L Smith (2016). "The contribution of the minimum wage to US wage inequality over three decades: a reassessment". In: *American Economic Journal: Applied Economics* 8.1, pp. 58–99.

Bárány, Zsófia L (2016). "The minimum wage and inequality: the effects of education and technology". In: *Journal of Labor Economics* 34.1, pp. 237–274.

Bradley, David H (2017). "The Federal Minimum Wage: In Brief (CRS Report R43089)". In:

Brucker, Debra L et al. (2015). "More Likely to Be Poor Whatever the Measure: Working-Age Persons with Disabilities in the United States*". In: *Social Science Quarterly* 96.1, pp. 273–296.

Burdett, Kenneth and Dale T Mortensen (1998). "Wage differentials, employer size, and unemployment". In: *International Economic Review*, pp. 257–273.

Burkhauser, Richard V and David C Stapleton (2004). "The decline in the employment rate for people with disabilities: Bad data, bad health, or bad policy?" In: *Journal of Vocational Rehabilitation* 20.3, pp. 185–201.

Card, David and Alan B Krueger (1994). "Minimum Wages and Employment: A Case Study of the Fast-Food Industry in New Jersey and Pennsylvania". In: *The American Economic Review* 84.4, pp. 772–793.

DOL, U.S. Department of Labor: (2012). *Fact Sheet 39: The Employment of Workers with Disabilties at Subminimum Wages*. URL: https://www.dol.gov/whd/regs/compliance/whdfs39.htm.

Dube, Arindrajit, T William Lester, and Michael Reich (2016). "Minimum wage shocks, employment flows, and labor market frictions". In: *Journal of Labor Economics* 34.3, pp. 663–704.

Flabbi, Luca (2010). "Gender discrimination estimation in a search model with matching and bargaining". In: *International Economic Review* 51.3, pp. 745–783.

Flinn, Christopher J (2011). *The minimum wage and labor market outcomes*. MIT press.

GAO, Government Accountability Office: (2001). *Special Minimum Wage Program: Centers Offer Employment and Support Services to Workers With Disabilties, But Labor Should Improve Oversight (GAO-01-886)*. Tech. rep.

Gorry, Aspen (2013). "Minimum wages and youth unemployment". In: *European Economic Review* 64, pp. 57–75.

Houtenville A.J., Brucker D.L. and E. Lauer (2014). *Annual Compendium of Disability Statistics: 2014*.

Kavanagh, Anne M et al. (2015). "Intersections between disability, type of impairment, gender and socio-economic disadvantage in a nationally representative sample of 33,101 working-aged Australians". In: *Disability and health journal* 8.2, pp. 191–199.

Kraus L., Lauer E. Coleman R. and A.J. Houtenville (2018). *2017 Disability Statistics Annual Report*.

Laditka, James N and Sarah B Laditka (2017). "Work Disability in the United States, 1968–2015: Prevalence, Duration, Recovery, and Trends". In: *SSM-population health*.

Langford, Christopher R, Mark L Lengnick-Hall, and Mukta Kulkarni (2013). "How Do Social Networks Influence the Employment Prospects of People with Disabilities?" In: *Employee responsibilities and rights Journal* 25.4, pp. 295–310.

Lauer, E.A. and A.J. Houtenville (2017). *Annual Disability Statistics Compendium: 2016*.

Mann, David R and David C Wittenburg (2015). "Starting behind: Wage and employment differentials between young adults with and without disabilities". In: *Journal of Disability Policy Studies* 26.2, pp. 89–99.

Meer, Jonathan and Jeremy West (2015). "Effects of the minimum wage on employment dynamics". In: *Journal of Human Resources*.

Meyer, Bruce D and Wallace KC Mok (2013). *Disability, Earnings, Income and Consumption*. Tech. rep. National Bureau of Economic Research.

Mitra, Sophie and Douglas Kruse (2016). "Are workers with disabilities more likely to be displaced?" In: *The International Journal of Human Resource Management* 27.14, pp. 1550–1579.

Neumark, David, Mark Schweitzer, and William Wascher (2004). "Minimum wage effects throughout the wage distribution". In: *Journal of Human Resources* 39.2, pp. 425–450.

Raise the Wage Act (S. 1242), 115th Congress (2017). URL: https://www.congress.gov/bill/115th-congress/senate-bill/1242/text.

Ryan, Camille L and Kurt Bauman (2016). "Educational attainment in the United States: 2015". In: *Current Population Reports* 20.

SSA, U.S. Social Security Administration (2017). *Disability Benefits*. URL: https://www.ssa.gov/pubs/EN-05-10029.pdf.

Wolpin, Kenneth I (1987). "Estimating a structural search model: the transition from school to work". In: *Econometrica: Journal of the Econometric Society*, pp. 801–817.