I Z A Institute of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 13020

Bounding the Joint Distribution of Disability and Employment with Contaminated Data

Ding Liu
Daniel L. Millimet

FEBRUARY 2020

I Z A Institute of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 13020

Bounding the Joint Distribution of Disability and Employment with Contaminated Data

Ding Liu
Southern Methodist University

Daniel L. Millimet
Southern Methodist University and IZA

FEBRUARY 2020

ISSN: 2365-9793

IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

Bounding the Joint Distribution of Disability and Employment with Contaminated Data

Understanding the relationship between disability and employment is critical and has long been the subject of study. However, estimating this relationship is difficult, particularly with survey data, since both disability and employment status are known to be misreported. Here, we use a partial identification approach to bound the joint distribution of disability and employment status in the presence of contaminated data. Allowing for a modest amount of contamination leads to bounds on the labor market status of the disabled that are not overly informative given the relative size of the disabled population. Thus, absent further assumptions, even a modest amount of contamination creates much uncertainty about the employment gap between the non-disabled and disabled. However, additional assumptions considered are shown to have some identifying power. For example, under our most stringent assumptions, we find that the employment gap is at least 15.2% before the Great Recession and 22.0% afterwards.

JEL Classification: C14, C18, J14, J64

Keywords: employment, disability, measurement error, partial identification

Corresponding author:
Daniel Millimet
Department of Economics
Box 0496
Southern Methodist University
Dallas
USA

E-mail: millimet@smu.edu

1 Introduction

The relationship between disability status and labor market outcomes is crucial to understanding the costs associated with poor health. It is also informs disability policies such as the American with Disabilities Act (ADA) passed in 1990 and the ADA Amendments Act (ADAAA) passed in 2008. This connection has not been lost on policymakers, as the "indirect labor productivity costs associated with poor health and chronic disease has raised the interest of policymakers" (Leroux et al. 2012, p. 526). Unfortunately, our knowledge is limited. Meyer and Mok (2019, p. 51) state: "Despite high disability rates and high costs, there are major gaps in our understanding of the economic consequences of disability." A primary reason for such gaps in our knowledge is reliance on contaminated data. Contamination arises because data on disability status and labor market outcomes are typically self-reported, leading to significant misclassification in survey data. Here, we investigate what can be learned about the labor market status of the disabled and non-disabled under minimal and transparent assumptions in a partial identification framework.

That data contamination is a significant concern when assessing *both* disability status and labor market outcomes is not new. In terms of disability, Kreider and Pepper (2007, p. 432) note that "there is widespread concern about the accuracy of self-reported disability status in survey datasets." Gosling and Saloniki (2014, p. 1085) find a "strong estimated bias" in the employment gap between the non-disabled and the disabled using a self-reported measure disability status similar to ours. This contamination reflects many underlying causes, the most obvious which is a lack of an agreed upon definition of disability and a corresponding appropriately worded survey question, leading to subjectiveness in the understanding of concepts such as disability or work limitation (Hale 2001; Baker et al. 2004). Other reasons include intentional misreporting due to economic or psychological incentives (Bound and Burkhauser 1999; Kreider and Pepper 2007; Gosling and Saloniki 2014), such as stigma (Kruse and Schur 2003) or as a rationalization for a lack of employment, a concept known as the "justification hypothesis" (Baker et al. 2004; Kreider and Pepper 2008; Leroux et al. 2012). Although self-reported disability status may be contaminated, it is arguably preferred to disability defined on the basis of disability benefits under Social Security Disability Insurance (SSDI) or Supplementary Security Income (SSI). As stated in Meyer and Mok (2019), not all disabled individuals are likely to apply for benefits, benefits may be misreported in surveys also, benefit eligibility incorporates other criteria such as assets and/or work history, and benefit decisions may be erroneous (see also Low and Pistaferri 2019).

In terms of labor market status, there is equally strong evidence of contamination in survey data. Feng et al. (2018, p. 1) state that "it is well-known that labor force statuses in survey data are subject to measurement errors." In particular, unemployment is likely under-reported, with these individuals being incorrectly classified as either employed or out of the labor force. Feng and Hu (2013, p. 1067) write that "most of the misclassification errors are from the unemployed people misreporting their labor force status as either employed or not-in-labor-force." This is consistent with older evidence suggesting that 10% of unemployed individuals are misclassified, while only 1% of employed or labor force nonparticipants are misclassified (Abowd and Zellner 1985). Moreover, Feng and Hu (2013, p. 1069) conclude that misclassification errors "at least partly reflect the intrinsic difficulties in classifying labor force statuses of certain groups of people, such as marginally attached workers." While the authors do not explicitly consider the disabled, it is quite possible that misclassification rates among the disabled are similar to those for marginally attached workers. Other studies using various data sources and approaches to document misclassification in self-reported labor market status include Poterba and Summers (1986), Chua and Fuller (1987), Magnac and Visser (1999), Keane and Sauer (2009), Abraham et al. (2013), and Hyslop and Townsend (2017).[1]

Assessing how labor market outcomes vary with disability status while allowing for contamination in both variables is not trivial. Existing studies investigating this issue and accounting for some contamination focus exclusively on misclassification of disability status. Misclassification of labor market status is ignored. Kreider and Pepper (2007), in the study most similar to ours, bound the employment gap between the non-disabled and the disabled using a partial identification approach. The authors allow for partial verification of disability status in a subset of their sample and then assume a maximum degree of contamination in the unverified remainder. Kreider and Pepper (2007) also explore the identifying power of the monotone instrumental variable (MIV) assumption proposed in Manski and Pepper (2000). Leroux et al. (2012) use propensity score matching to compare the associations between health status and labor force participation when health status is self-reported as opposed to reported by a proxy. The authors interpret differences as reflecting contamination, where proxies are potentially more reliable as they may face fewer psychological incentives to mis-report (e.g., less stigma or compulsion to justify the non-employment of others). Gosling and Saloniki (2014) obtain point estimates of the employment gap between the non-disabled and the disabled. In contrast to Kreider and Pepper (2007), the authors impose a set of stronger assumptions: (i) the presence of two mismeasured reports of disability status with independent measurement errors, (ii) the expected employment gap is not zero, and (iii) misclassification of disability status is independent of (self-reported) employment. Gosling and Saloniki (2014, p. 1095) conclude: "Clearly some will disagree with the assumptions made in this paper, and thus, a possible future avenue for research will be to develop a methodology allowing this to be weaker."

We take this call for future research to heart by weakening the assumptions considered in Gosling and Saloniki (2014). We first explore what can be learned under minimal assumptions. We then gradually

[1] Administrative data is not a panacea for data contamination. First, administrative data is limited, and requires both disability and labor market status information for the question at hand. Second, even with administrative data, misclassification cannot be ignored (e.g., Hyslop and Townsend 2017).

add stronger assumptions to assess their identifying power. Some of our assumptions overlap Kreider and Pepper (2007), but we also consider others not present in their study. Most importantly, unlike Kreider and Pepper (2007) and Gosling and Saloniki (2014), we also allow for contamination in self-reported labor market status. Our methodology is similar to Gundersen and Kreider (2008). There, the authors partially identify the prevalance of food insecurity among food stamp recipients allowing contamination in both food insecurity and food stamp recipiency. We also use methods recently developed in Millimet et al. (2019) and Li et al. (2019).

To proceed, we use data from the Survey of Income and Program Participation (SIPP) covering three time periods: January 2004, August 2009, and October 2013. The choice of these months is based in part on maximizing sample size. In addition, January 2004 is before the Great Recession and passage of the ADAAA, August 2009 is at the height of the Great Recession and shortly after the passage of the ADAAA, and October 2013 is during the recession recovery and several years after the passage of the ADAAA. Both the Great Recession and the ADAAA may have altered the relationship between disability status and labor market outcomes. The ADAAA, by broadening the definition of disability, may have changed this relationship given early studies of the ADA that find that the employment protections conferred to the disabled may have depressed both the hiring and firing rates of such individuals (DeLiere 2000; Acemoglu and Angrist 2001; Kim and Rhee 2018). Moreover, the Great Recession and the ADAAA may impact the amount of data contamination. For example, Feng and Hu (2013) find lower overall levels of misclassification in labor market status during the Great Recession.

Our analysis yields three important findings. First, it is critical to account for misclassification when assessing how labor market status varies with disability status. Allowing for misclassification rates in line with prior evidence adds considerable uncertainty to the estimated conditional probabilities and especially estimates of the employment and unemployment gaps. Second, the assumptions considered here are sufficient to considerably tighten the bounds on the conditional probabilities for the non-disabled, less so for the disabled. Nonetheless, we are able to learn a considerable amount about the disabled, and we are able to sign the employment gap. Finally, while not definitive, comparison of the bounds before and after the Great Recession suggests that the labor market may have worsened over this span for the disabled. This may be attributable to a disproportionate adverse impact of the recession on the disabled or the passage of the ADAAA.

The rest of the paper is organized as follows. Section 2 presents our partial identification approach. Section 3 introduces the data. Section 4 discusses the results. Section 5 concludes.

2 Methods

2.1 Setup

Let d_i^* denote the true disability status and y_i^* denote the true labor market status for observation i, $i = 1, ..., N$. Both variables are binary, where we assign the value of one to d^* to denote the presence of a disability and a value of one to y^* to denote lower labor market participation (i.e., nonemployment, unemployment, or nonparticipation). These will be explicitly defined in Section 3. Further, let $f(d^*, y^*)$ denote the joint (bivariate) distribution. This distribution can be written as a 2×2 matrix, P^*, given by

$$P^* = \begin{bmatrix} p_{00}^* & p_{01}^* \\ p_{10}^* & p_{11}^* \end{bmatrix}. \tag{1}$$

Elements of this matrix have the following form

$$p_{kl}^* = \frac{\Pr(d^* = k, y^* = l)}{\Pr(d^* = k)} \qquad k, l = 0, 1. \tag{2}$$

Thus, p_{kl}^* is a conditional probability. Finally, we can define conditional joint distribution, conditioned upon $X = x$, where X denotes a vector of observed attributes. Denote the conditional matrix as $P^*(x)$, with elements given by

$$p_{kl}^*(x) = \frac{\Pr(d^* = k, y^* = l | X = x)}{\Pr(d^* = k | X = x)} \qquad k, l = 0, 1. \tag{3}$$

Given the definition of P^* or $P^*(x)$, our objective is to learn something about its elements. With a random sample $\{d_i^*, y_i^*, x_i\}$, the probabilities in (1) are point identified as they are functions of nonparametrically estimable quantities. The corresponding plug-in estimator is consistent. However, as stated previously, ample evidence indicates that labor market and disability status are measured with error. Let d_i and y_i denote the observed disability and labor market statuses for observation i, respectively. With data $\{d_i, y_i, x_i\}$, the empirical probabilities are inconsistent for p_{kl}^* and $p_{kl}^*(x)$.

With access only to contaminated data, our goal is to bound the probabilities given in (2) and (3). The relationships between the true labor market and disability statuses, $\{d_i^*, y_i^*\}$, and the observed statuses,$\{d_i, y_i\}$, are characterized by the following joint probabilities:

$$\theta_{kl}^{k'l'} = \Pr(d = k',\ y = l',\ d^* = k,\ y^* = l). \tag{4}$$

While conditional misclassification probabilities are more intuitive, these joint probabilities are easier to work with (e.g., Kreider et al. 2012).

In (4) the subscript kl indexes the true disability and labor market statuses and the superscript $k'l'$

indicates the observed disability and labor market statuses. θ_{kl}^{kl} represents the probability of no contamination for an observation with true labor market status k and true disability status l. With this notation, we can rewrite the elements of P^* as

$$\begin{aligned} p_{kl}^* &= \frac{\Pr(d^* = k, y^* = l)}{\Pr(d^* = k)} \\ &= \frac{\Pr(d = k, y = l) + \sum\limits_{\substack{k',l'=0,1 \\ (k',l')\neq(k,l)}} \theta_{kl}^{k'l'} - \sum\limits_{\substack{k',l'=0,1 \\ (k',l')\neq(k,l)}} \theta_{k'l'}^{kl}}{\Pr(d = k) + \sum\limits_{\substack{k',l',\tilde{l}=1,2,\ldots,K \\ k'\neq k}} \theta_{k\tilde{l}}^{k',l'} - \sum\limits_{\substack{k',l',\tilde{l}=1,2,\ldots,K \\ k'\neq k}} \theta_{k'\tilde{l}}^{kl'}} \\ &\equiv \frac{r_{kl} + Q_{1,kl} - Q_{2,kl}}{p_l + Q_{3,k} - Q_{4,k}}. \end{aligned} \tag{5}$$

The expression in (5) is identical to that in Gundersen and Kreider (2008, p. 368). $Q_{1,kl}$ measures the proportion of false *negatives* associated with partition kl (i.e., the probability of being misclassified conditional on kl being the true partition). $Q_{2,kl}$ measures the proportion of false *positives* associated with partition kl (i.e., the probability of being misclassified conditional on kl being the observed partition). Similarly, $Q_{3,k}$ and $Q_{4,k}$ measure the proportion of false *negatives* and *positives* associated with disability status k, respectively.

The conditional probabilities in (5) are not identified from the data alone. The data identify r_{kl} and p_k (and, hence, $p_{kl} \equiv r_{kl}/p_k$), but not the misclassification parameters, θ. One can compute sharp bounds by searching across the unknown misclassification parameters. There are 12 misclassification parameters in P^*. However, several constraints must hold (Millimet et al. 2019). Even with these constraints, obtaining informative bounds on the transition probabilities is not possible without further restrictions. Section 2.2 considers assumptions on the θs. Section 2.3 considers restrictions on the underlying data generation process (i.e., the relationship between labor market and disability status).

2.2 Contamination

2.2.1 Assumptions

Allowing for contamination, we obtain bounds on the elements of P^* given in (5).[2] To proceed, we consider the following misclassification assumptions, similar to those considered in Gundersen and Kreider (2008), Millimet et al. (2019), and Li et al. (2019).

Assumption 1 (Maximum Misclassification Rate)**.** *The total misclassification rate in the data is bounded*

[2] In the interest of brevity, we focus on the elements of P^*. In Section 2.3 we will discuss elements of $P^*(x)$.

from above by $Q \in (0,1)$. Formally, $1 - \sum_{k,l} \theta_{kl}^{kl} \leq Q$ or, equivalently,

$$\sum_{\substack{k,k',l,l'=0,1 \\ k'l' \neq kl}} \theta_{kl}^{k'l'} \leq Q.$$

Assumption 2 (Orthogonal Misclassification)**.** *Misclassifications across labor market and disability status are orthogonal. Formally,*

$$\theta_{kl}^{k'l'} \equiv \alpha_k^{k'} \bullet \beta_l^{l'},$$

where $\alpha_k^{k'}$ ($\beta_l^{l'}$) is the probability of being observed in labor market (disability) status k' (l') when the true status is k (l).

Assumption 1 places restrictions on the total amount of contamination allowed in the data. Placement of an upper bound on the probability of a data error in robust estimation is suggested in Horowitz and Manski (1995). In our context, recall there are 12 misclassification parameters. Assumption 1 limits the sum of these parameters, but not the number of parameters. In particular, this assumption does not impose that self-reported disability or employment rates overstate true rates; the misclassification is allowed to be completely arbitrary. As argued in Burkhauser et al. (2002), self-reported disability may undertstate the true incidence. As discussed above, Feng and Hu (2013) find that unemployment is under-reported, with both employment and nonparticipation being over-reported.

In our baseline analysis, we set $Q = 0.10$. Considering 10% contamination seems like a reasonable choice; however, we vary Q from zero to 0.40 to explore the sensitivity to this choice. Hampel et al. (1986. p. 28) state "altogether, 1-10% gross errors in routine data seem to be more the rule rather than the exception." Considering self-reported labor market status in isolation, Feng and Hu (2013) estimate *conditional* misreporting rates of 2.1% for the 'truly' employed, 37.5% for the 'truly' unemployed, and 3.1% for the 'truly' labor force nonparticipants. Assuming 70% of their sample is 'truly' employed and 10% (20%) are 'truly' unemployed (labor force nonparticipants), this corresponds to an *unconditional* misreporting rate of 5.8%. Similarly, Magnac and Visser (1999) suggests around 6% misreporting in labor force participation. However, other studies suggest less contamination. Keane and Sauer (2009) estimate an unconditional misreporting rate of 1.3% to 1.8%. The data in Table 1 in Chua and Fuller (1987) indicate a 3.2% misclassification rate for a binary measure of employment status, whereas Table II in Poterba and Summers (1985) documents a 3.9% misreporting rate for employment status. Considering self-reported disability in isolation, Kreider and Pepper (2007) allow for a maximum misreporting rate of 6.7%. Gosling and Saloniki (2014) estimate *conditional* misreporting rates of 17.4% for the 'truly' disabled and 1.5% for the 'truly' non-disabled. Assuming a 'true' disability rate of 8%, this corresponds to an *unconditional* misreporting rate of 2.8%. Thus, a combined maximum error rate of 10% seems reasonable.

Assumption 2 states that the contamination probabilities for labor market and disability status are orthogonal. This assumption reduces the number of misclassification parameters from 12 to 4. Assumption 2 is similar in spirit to the the assumption of orthogonal errors considered in Gundersen and Kreider (2008). However, in that study, misclassification errors are assumed to be orthogonal to the true value. Here, Assumption 2 still allows the probability of misclassification of d^* to depend on d^* (and similarly the probability of misclassification of y^* is allowed to depend on y^*). However, Assumption 2 rules out the possibility that the probability of misclassification of d^* depends on either y^* or y, and vice versa. In that sense, it is more similar to the assumption of Independent Classification Errors considered in Magnac and Visser (1999). There, classification errors in labor market status are assumed to be orthogonal across time periods. It is also similar to the assumption in Gosling and Saloniki (2014) that the misclassification of disability status is independent of self-reported employment status. Assumption 1 may be imposed with or without Assumption 2.

Assumption 2 is strong as there is some belief that, in particular, misreporting of disability status may be related to one's true labor market status (e.g., Kreider 1999). Moreover, Feng and Hu (2013) note that misclassification of labor market status is more likely for workers marginally attached to the labor force, which may include the disabled. However, Stern (1989) finds that self-reported disability is approximately exogenous in a model of labor force participation. Moreover, any correlation that may exist goes in the opposite direction; individuals working tend report worse health status due to stress. This type of relationship is not precluded by Assumption 2, but it does suggest that individuals do not appear to report a non-existent disability to rationalize not participating in the labor market.

2.2.2 Bounds

In the absence of contamination, consistent estimates are given by the empirical conditional probabilities (Proposition 1 in Millimet et al. (2019)):

$$\widehat{p}_{kl} = \frac{\sum_i \mathrm{I}(d_i = k, y_i = l)}{\sum_i \mathrm{I}(d_i = k)}.$$

Absent this assumption, the transition probabilities are no longer nonparametrically identified. Sharp bounds under Assumption 1 with or without Assumption 2.are detailed in Li et al. (2019).

2.3 Data-Generation Process

2.3.1 Assumptions

The preceding section provides bounds on the conditional probabilities considering only restrictions on the contamination process. Here, we introduce restrictions on the data-generation process governing true labor market and disability status that may further serve to tighten the bounds. The restrictions may be imposed alone or in combination.

First, we consider level set restrictions which place equality constraints on population conditional probabilities across observations with different observed attributes (Manski 1990; Lechner 1999).

Assumption 3 (Level Set Restrictions)**.** *The conditional transition probabilities, given in (3), are constant across a range of conditioning values. Formally, $p^*_{kl}(x)$ is constant for all $x \in \mathcal{A}_x \subset \mathcal{R}_m$, where x is an m-dimensional vector.*

In our analysis, we let x denote an individual's family non-labor income (per equivalent adult) discretized into several bins. We then assume that $p^*_{kl}(z)$ is constant for all z within a fixed window (plus or minus one bin) around x.

From (3) and (5), we have

$$\begin{aligned} p^*_{kl}(x) &= \frac{\Pr(d=k, y=l|X=x) + \sum\limits_{\substack{k',l'=0,1 \\ (k',l')\neq(k,l)}} \theta^{k'l'}_{kl}(x) - \sum\limits_{\substack{k',l'=0,1 \\ (k',l')\neq(k,l)}} \theta^{kl}_{k'l'}(x)}{\Pr(d=k|X=x) + \sum\limits_{\substack{k',l',\tilde{l}=1,2,\ldots,K \\ k'\neq k}} \theta^{k',l'}_{k\tilde{l}}(x) - \sum\limits_{\substack{k',l',\tilde{l}=1,2,\ldots,K \\ k'\neq k}} \theta^{kl'}_{k'\tilde{l}}(x)} \\ &\equiv \frac{r_{kl}(x) + Q_{1,kl}(x) - Q_{2,kl}(x)}{p_k(x) + Q_{3,l}(x) - Q_{4,l}(x)} \end{aligned} \tag{6}$$

where now $Q_{j,\cdot}(x)$, $j = 1, ..., 4$, represent the proportions of false positives and negatives conditional on x. As such, we also consider the following assumption regarding the conditional misclassification probabilities.

Assumption 4 (Independence)**.** *Misclassification rates are independent of the observed attributes of observations, x. Formally,*

$$\theta^{k'l'}_{kl}(x) = \theta^{k'l'}_{kl}, \ \forall k, k', l, l', x.$$

The plausibility of Assumption 4 depends on one's conjectures concerning the contamination process. However, two points are important to bear in mind. First, the misclassification probabilities, $\theta^{k'l'}_{kl}$, are specific to a pair of true and observed partitions. As a result, even if misclassification is more likely for the disabled or non-disabled or the employed or nonemployed and x is correlated with labor market and/or disability status, this does not necessarily invalidate Assumption 4. Second, Assumption 4 does not imply that misclassification rates are independent of all individual attributes, only those included in the variables used to define the level set restrictions. A similar assumption is imposed in Poterba and Summers (1995).

Second, we consider monotonicity restrictions which place inequality constraints on population conditional probabilities across observations with different observed attributes (Manski and Pepper 2000; Chetverikov et al. 2018).

Assumption 5 (Monotonicity). *The conditional probability of strong labor market participation is weakly decreasing in a vector of attributes, u, and the conditional probability of weak labor market participation is weakly increasing in the same vector of attributes. Formally, if $u_2 \geq u_1$, then*

$$\begin{aligned} p^*_{00}(u_1) &\geq p^*_{00}(u_2) \\ p^*_{10}(u_1) &\geq p^*_{10}(u_2) \\ p^*_{01}(u_1) &\leq p^*_{01}(u_2) \\ p^*_{11}(u_1) &\leq p^*_{11}(u_2). \end{aligned}$$

In our analysis, we let u denote an individual's age discretized into several bins. We then assume that the probability of strong labor market participation is no lower (higher) for younger (older) individuals conditional on true disability status.

2.3.2 Bounds

The bounds under various combinations of Assumptions 1 – 5 are provided in Li et al. (2019). However, as discussed in Millimet et al. (2019), estimates of the bounds suffer from finite sample bias as they rely on infima and suprema. To circumvent this issue, we follow this previous work and utilize a bootstrap bias correction, based on subsampling with replicate samples of size $N/2$. To obtain confidence intervals, we utilize subsampling along with the Imbens-Manski (2004) correction to obtain 90% confidence intervals (CIs).[3] As with the bias correction, we set the size of the replicate samples to $N/2$.

3 Data

To assess the relationship between disability and labor market status, we use data from the SIPP. Collected by the US Census Bureau, SIPP is a rotating, nationally representative longitudinal survey of households. Begun in 1984, SIPP collects detailed income data as well as data on a host of other economic and demographic attributes. Households in the SIPP are surveyed over a multi-year period ranging from two and a half years to four years. Then, a new sample of households are drawn. The sample sizes range from approximately 14,000 to 52,000 households. Here, we use the 2004, 2008, and 2014 panels to examine the relationship between disability and labor market status before, during, and after the Great Recession. For the 2004 panel, data are from January 2004. For the 2008 panel, data are from August 2009. For the 2014 panel, data are from October 2013. In addition to the Great Recession, the American with Disabilities

[3] The literature on inference in partially identified models is expanding rapidly. However, as discussed in Millimet et al. (2019), the Imbens-Manski (2004) approach is preferable in the current context.

Act Amendments Act (ADAAA) was signed into law in 2008 and become effective on January 1, 2009. The ADAAA made a number of significant changes to the definition of disability. Thus, the relationship between disability and labor market status, as well as what can be learned about the relationship in the presence of contamination, may have changed across three time periods analyzed.

In terms of thinking about contamination, it is necessary to understand the length of recall in the data. For the January 2004 data, respondents were interviewed in February to May 2004 with equal numbers interviewed in each month. Thus, the average length of recall was about three months. Similarly, for the August 2009 data, respondents were interviewed in September to December 2010. Again, the average length of recall was about three months. In 2014, the data collection process for the SIPP changed. Here, for the October 2013 data, respondents were interviewed sometime between February and June 2014. Thus, the average length of recall was about six months. Depsite the longer recall period, we use the data from October 2013 to avoid temporary changes in labor market status during the holidays in November and December 2013.

For the analysis, labor market status is derived from the employment status recode variable for the month (variable RMSER). This variable takes on eight values: (1) with a job all month, worked all weeks; (2) with a job all month, without pay 1+ weeks not due to layoff; (3) with a job all month, without pay 1+ weeks due to layoff; (4) with a job 1+ but not all weeks, no layoff or time spent looking for work; (5) with a job 1+ but not all weeks, time spent on layoff or looking for work; (6) no job all month, on layoff or looking for work all weeks; (7) no job all month, on layoff or looking for work 1+ but not all weeks; and, (8) no job all month, no layoff or time spent looking for work. We construct three measures of labor market status from this variable: *Nonemployed* (y equals one for responses 6-8, zero otherwise); *Unemployed* (y equals one for responses 6-7, zero for responses 1-5); and, *Nonparticipant* (y equals one for response 8, zero otherwise). Here, y may differ from y^* due to intentional misreporting, as well as imperfect recall.

Disability status is based on whether respondents had a "physical, mental, or other health condition that limits the kind or amount of work" one can perform (variable EDISABL). d equals one for those reporting the presence of such a condition, zero otherwise. Aside from intentional misreporting, d may differ from d^* for two reasons (Hale 2001). First, respondents with temporary health issues, such as a broken leg, would be correct in responding in the affirmative. Second, the wording only inquires about disabilities or health conditions that limit work. However, the ADA definition of disability does not presume that a person with a disability must be limited or unable to work. Both of these flaws stem from the fact that "arriving at a satisfactory definition of disability ... is in fact not easily achieved" (Wilkins 2004, p. 362).

We restrict the estimation sample to individuals between 25 and 69 years old with non-missing data.[4]

[4] Kreider and Pepper (2007) focus on individuals age 40-69, while other studies such as Wilkins (2004) and Meyer and Mok (2019) consider younger individuals as well. Gosling and Saloniki (2014) analyze individuals age 21-59. Leroux et al. (2012) include individuals age 18-65.

When using *Nonemployed* or *Nonparticipant* to measure labor market status, the sample size for the 2004 panel is 61,171; 51,429 for the 2008 panel; 40,991 for the 2014 panel. Summary statistics are presented in Table 1.

When imposing level set restrictions, we use per capita monthly non-labor income. This variable is defined as total family income less family labor income. The measure is then converted to per capita terms using the OECD equivalence scale.[5] Finally, the variable is discretized into five categories: (1) Negative (less than 0.1); (2) Extremely Small (0.1 to 10); Small (10 to 200); Medium (200 to 725); Large (greater than 725). These values roughly correspond to quintiles. Our level set restriction then assumes that the conditional probabilities are constant across adjacent bins. For example, we tighten the bounds on p^*_{kl} for individuals with, say, 'small' per capita monthly non-labor income by assuming that p^*_{kl} is constant across individuals with 'extremely small', 'small, and 'medium' per capita monthly non-labor income. When imposing the monotonicity restrictions, we use the age of the individual (variable TAGE) as in Kreider and Pepper (2007). Here, individuals are grouped into five bins, each bin spanning nine years.

Table 1 presents summary statistics. The sample employment rate decreases from 0.73 in the 2004 panel, to 0.70 in the 2008 panel, and to 0.67 in the 2014 panel. The sample disability rate is 0.14 in the 2004 panel; 0.16 in the 2008 and 2014 panels. This is in line with figures reported in Meyer and Mok (2019) and elsewhere. As for the conditional employment rates, they are declining across the time periods. The employment rate for the disabled falls from 0.287 to 0.271 to 0.218 across the three time periods. Similarly, the employment rate for the non-disabled decreases from 0.799 to 0.777 to 0.756.

4 Results

The results are presented in Tables 2-7 and Figures A1-A12 in the supplemental appendix. Tables 2-3 and Figures A1-A4 contain the results using *Nonemployed* to measure labor market status. Tables 4-5 and Figures A5-A8 contain the results using *Nonparticipant* to measure labor market status. Finally, Tables 6-7 and Figures A9-A12 contain the results using *Unemployed* to measure labor market status. For each measure of labor market status, the first table contains the point estimates of the conditional probabilities under the assumption of no misclassification and the bounds under Assumption 1 with or without Assumption 2. The second table displays the bounds under various combinations of Assumptions

[5] Formally, the variable is constructed as

$$\frac{1}{N}\left(M_1 - M_2\right),$$

where M_1 is total family income (variable TFTOTINC), M_2 is family labor income (variable TFEARN), and N is the number of adult equivalents in the family, given by

$$N = 1 + 0.7(N_1 - 1 - N_2) + 0.5N_2,$$

where N_1 is the number of adults in the family (variable EFNP) and N_2 is the number of children less than 18 years old in the family (variable RFNKIDS).

1 – 5. The first three figures for each measure of labor market status graph the bounds for the three different time periods under various assumptions as Q varies from zero to 0.40; the final figure graphs the bounds on the gap between the non-disabled and disabled.

Turning to the results for employment, Panel I in Table 2 indicates that the probability of being employed is 0.799 for the non-disabled in the 2004 sample, declining to 0.777 and 0.770 in the 2008 and 2014 samples, respectively. For the disabled, the corresponding probabilities are 0.287, 0.271, and 0.208. Thus, the self-reported employment gap changes across the three time periods from 0.512 to 0.506 to 0.562. The jump in the gap in the 2014 panel is noticeable given the studies mentioned earlier that find reduced employment of the disabled following the implementation of the ADA. However, clearly this is not meant to be taken as evidence of a causal effect of the ADAAA even absent data contamination. In particular, prior evidence suggests that the disabled are disproportionately affected by tight labor markets, which likely characterizes this period of early recovery from the Great Recession (Kruse and Schur 2003).

Panel II (Panel III) allows for contamination, but imposes Assumption 1 (Assumptions 1 and 2) setting $Q = 0.10$. Under Assumption 1 the bounds are completely uninformative for the disabled in the 2004 Panel. For the other two panels, the bounds are modestly informative as the bounds are smaller than the unit interval. Nonetheless, this is indicative of how small amounts of (arbitrary) data contamination leads to tremendous uncertainty in the conditional probabilities for the disabled given the small fraction of self-reported disabled. Specifically, the conditional probability of employment for the disabled is [0.000,1.000], [0.000,0.915], and [0.000,0.853] across the three time periods.[6] The conditional probability of non-employment for the disabled is [0.000,1.000], [0.085,1.000], and [0.147,1.000] across the three time periods. Although wide, the increase in the lower bound over time is striking; at least 14.7% of the disabled are non-employed in the 2014 panel.

The corresponding bounds under Assumption 1 for the non-disabled are more informative, owing to the larger proportion of self-reported non-disabled. The conditional probability of employment for the non-disabled is [0.682,0.915], [0.659,0.896], and [0.652,0.888] across the three time periods. The conditional probability of non-employment for the non-disabled is [0.085,0.318], [0.104,0.341], and [0.112,0.348] across the three time periods. Although more informative than the bounds for the disabled, the width of the bounds indicates the importance of accounting for data contamination. Even relatively small amounts of misclassification undercuts the certainty of what can be learned. Treating the self-reported data as error-free gives rise to what Manski (2011) refers to as "incredible certitude." However, even relaxing the assumption of error-free data, it is noteworthy that the lower bound on the probability of non-employment for the non-disabled (disabled) rises from 0.104 to 0.112 (0.085 to 0.147) across the 2008 and 2014 panels.

[6] Throughout our discussion, we focus on the point estimates of the bounds. The confidence intervals for the bounds are slightly wider.

Again, this is *consistent* with the ADAAA reducing employment opportunities for the disabled, or the disabled being disproportionately affected in the aftermath of the Great Recession.

Assumption 2 has significant identifying power as the bounds in Panel III are much narrower. Now, the conditional probability of employment for the disabled is [0.000,0.647], [0.000,0.593], and [0.000,0.531] across the three time periods. The conditional probability of non-employment for the disabled is [0.353,1.000], [0.407,1.000], and [0.469,1.000] across the three time periods. For the non-disabled, the conditional probability of employment is [0.741,0.857], [0.718,0.836], and [0.711,0.829] and the conditional probability of non-employment for the disabled is [0.143,0.259], [0.164,0.282], and [0.171,0.289] across the three time periods. Given the narrowing of the bounds, we find that the employment gap is strictly positive in all three time periods. For example, in the 2004 panel, the employment rate for the non-disabled (disabled) is at least (at most) 0.741 (0.647). Thus, the employment gap in this time period is at least $0.741 - 0.647 = 0.094$; the gap is at least 0.125 and 0.180 in the other two time periods. The corresponding upper bounds on the employment gap are 0.857, 0.836, and 0.829.

Table 3 displays the bounds incorporating additional assumptions. Panel IA imposes Assumptions 1, 3, and 4; Panel IB adds Assumption 5. Panel IIA imposes Assumptions 1, 2, 3, and 4; Panel IIB adds Assumption 5. The results reveal that each of the assumptions considered has identifying power, with perhaps the monotonicity assumption adding the least (see Figures A1-A3). For example, the conditional probability of employment for the disabled in the 2004 panel narrows from [0.000,1.000] in Panel II of Table 2 to [0.000,0.743] in Panel IB of Table 3. Thus, under the level set and monotonicity assumptions, we find that the *maximum* possible employment rate for the disabled is 74.3% in the first time period; 73.5% and 72.7% in the 2008 and 2014 panels, respectively. The conditional employment probabilities for the non-disabled also narrow when imposing additional assumptions. Under the level set and monotonicity assumptions (Panel IB), we find that the *minimum* possible employment rate for the non-disabled is 74.6% in the first time period; 73.5% and 74% in the 2008 and 2014 panels, respectively. Together, these bounds imply that the employment gap is at least 0.003, 0, and 0.013 across the three time periods under the level set and monotonicity assumptions. See also Figure A4.

Assumption 2 continues to have identifying power when imposed in addition to the assumptions used in Panel I of Table 3. Interestingly, it appears that the monotonicity assumption has more identifying power when imposed in conjuction with Assumption 2 (see Figures A1-A3). For example, the conditional employment probability for the disabled narrows from [0.000,0.743] in Panel IB for the 2004 panel to [0.068,0.631] in Panel IIB. Similarly, the conditional employment probability for the non-disabled narrows from [0.746,0.824] in Panel IB for the 2004 panel to [0.783,0.792] in Panel IIB. Thus, under our most stringent set of assumptions, we find that the *maximum* possible employment rate for the disabled is 63.1% in the first time period; 59.3% and 53.1% in the 2008 and 2014 panels, respectively. The *minimum* possible employment rate for the non-disabled is 78.3% in the first time period; 74.5% and 75.1% in the 2008 and 2014 panels, respectively. The employment gap is at least 0.152, 0.162, and 0.220 across the three time periods (see Figure A4).

Finally, Figures A1-A4 show the effect of varying the maximum contamination rate, Q, on select bounds. There are several general takeaways. First, for a given Q, Assumptions 2, 3, 4, and 5 have identifying power. Thus, to the extent that one finds these assumptions plausible, they add to what can be learned about the conditional probabilities in the presence of data contamination. Second, the bounds for the disabled are quite sensitive to Q. Moreover the bounds widen quickly as Q increases from zero to 0.10 and then more gradually thereafter. Consequently, researchers should be wary of dismissing data contamination because the problem is likely to be 'small.' Third, the bounds for the non-disabled are also sensitive to the choice of Q, but less so given the larger proportion of non-disabled. Moreover, under the level set and monotonicity assumptions, the bounds are fairly narrow for values of Q between zero and 0.10; after this, the bounds begin to widen more quickly with further increases in Q. Fourth, the bounds for the non-disabled under our most stringent set of assumptions often exclude the rate reported in the data. For example, in Panel IIB of Table 3, the bounds on the conditional probability of employment for the non-disabled in the 2004 and 2008 panels exclude the corresponding sample employment rate reported in Panel I of Table 2. Although difficult to see, this is shown in Panels A and B in Figures A1 and A2. Thus, if one believes this set of assumptions, then the self-reported value cannot be the true value, revealing the cost of ascribing incredible certitude on the observed data.[7] Finally, under our most stringent set of assumptions, bounds on the employment gap exclude zero for Q roughly up to 0.20 in all three time periods. Under weaker assumptions, thr bounds exclude zero only for Q up to around 0.10. Under no assumptions, a misclassification rate of 0.07 or so is sufficient to preclude signing the employment gap.

Tables 4-5 and Figures A5-A8 display the results for labor market participation. The results are generally similar to those for employment. In particular, under Assumptions 1 and 2 (Table 4, Panel III), the labor force participation gap is [0.102,0.891], [0.139,0.894], and [0.156,0.869] across the three time periods. Under Assumptions 1, 3, 4, and 5 (Table 5, Panel IB), the gap is [0.016,0.890], [0.014,0.889], and [-0.009,0.878]. Under our most stringent set of assumptions (Table 5, Panel IIB), the gap is [0.154,0.746], [0.164,0.718], and [0.176,0.778]. Given the similarity to the bounds for employment versus non-employment, the choice between these two labor market measures is relatively inconsequential.

Tables 6-7 and Figures A9-A12 display the results for unemployment where the sample is restricted to those reporting to be in the labor force. Panel I in Table 6 indicates that the probability of being unemployed is 0.042 for the non-disabled in the 2004 sample, 0.069 in the 2008 sample, and 0.050 in the

[7] A similar result is obtained in Kreider and Pepper (2007), where their bounds sometimes exclude the self-reported value from the data. As we do here, the authors interpret this to imply that the self-reported data are error-ridden *if* one believes the assumptions used to derive the bounds.

2014 sample. For the disabled, the corresponding probabilities are 0.081, 0.138, and 0.237. Thus, the self-reported unemployment gap changes across the three time periods from -0.039 to -0.069 to -0.187. The change between the second and third time periods is even more noticeable than when examining employment or labor force participation.

Panel II (Panel III) allows for contamination, but imposes Assumption 1 (Assumptions 1 and 2) setting $Q = 0.10$. Under Assumption 1 the bounds are completely uninformative for the disabled in all time periods. The corresponding bounds under Assumption 1 for the non-disabled are informative. The conditional probability of unemployment for the non-disabled is [0.000,0.148], [0.000,0.176], and [0.000,0.156] across the three time periods. Imposing Assumption 2 narrows the bounds, particularly for the non-disabled. Now, the conditional probability of unemployment for the disabled is [0.000,0.959], [0.000,0.909], and [0.000,1.000] across the three time periods. For the non-disabled, the conditional probability of unemployment is [0.000,0.095], [0.015,0.122], and [0.000,0.103] across the three time periods. Despite the identifying power of Assumption 2, we are unable to sign the unemployment gap across the disabled and non-disabled; the bounds include zero.

Table 7 displays the bounds incorporating additional assumptions. While each assumption has some identifying power, only when we impose our most stringent set of assumptions do we substantially narrow the bounds on the parameters other than the conditional probability of employment for non-disabled. This arises because the majority of the sample self-reports into that strata (i.e., the combination of employed and non-disabled). Thus, for the remaining three strata, small amounts of (arbitrary) data contamination create substantial uncertainty in the conditional probabilities. Nonetheless, if one is willing to impose Assumptions 1 – 5 (Panel IIB), the conditional probability of unemployment for the disabled is [0.000,0.471], [0.000,0.535], and [0.000,0.677] across the three time periods. The conditional probability of employment for the disabled is [0.529,1.000], [0.465,1.000], and [0.323,1.000] across the three time periods. Interestingly, the *upper* bound on the conditional probability of employment versus non-employment for the disabled in Panel IIB of Table 3 is 0.631 in the 2004 panel. In Table 7, the corresponding *lower* bound for the conditional probability of employment versus unemployment is 0.529. This contrast illustrates the importance of thinking about the measure of labor market status when assessing the variation by disability status; in particular, the decision to focus on all individuals or just those reporting to be in the labor force.

For the non-disabled, under Assumptions 1 – 5, the conditional probability of unemployment is [0.030,0.074], [0.056,0.090], and [0.036,0.075] and the conditional probability of employment for the disabled is [0.926,0.970], [0.910,0.994], and [0.925,0.964] across the three time periods (Table 7, Panel IIB). While much information is learned under our most stringent set of assumptions, we are unable to sign the unemployment gap across the disabled and non-disabled; the bounds continue to include zero. We can, however, state that the *maximum* unemployment gap is 0.444, 0.479, and 0.641 across the three time periods. Thus, we cannot rule out quite large differences even under our strongest set of assumptions. Nonetheless, it is noteworthy that these upper bounds seem much lower than the point estimates obtained in Gosling and Saloniki (2014) obtained using data from the British Household Panel Survey. There, the employment gaps are around 0.70 on average.[8]

5 Conclusion

Meyer and Mok (2019, p. 51) state: "Disability may be the most significant risk that individuals and their families face. The prevalence of disability is high, its onset and persistence is largely unpredictable, and it is often permanent." Despite this, we still know relatively little about how the disabled fare in the labor market, and even less about the impact of the ADA and the subsequent ADAAA. Here, we explore what can be learned about how labor market status varies across the disabled and the non-disabled while confronting perhaps the most difficult econometric challenge: contamination in self-reported disability status *and* labor market status. To do so, we adopt a partial identification approach, pioneered in Horowitz and Manski (1995) and extended in Kreider and Pepper (2007), Gundersen and Kreider (2008), Millimet et al. (2019), and Li et al. (2019).

To implement our partial identification approach, we begin by imposing no assumption other than a maximum degree of arbitrary misclassification in the data. Based on prior evidence, we allow for up to 10% of the sample to be misclassified in at least one dimension, disability status or labor market status. In this case, we learn very little about the conditional probability of employment versus either non-employment or unemployment for the disabled. This arises because a 10% misclassification, although modest as a proportion of the entire sample, is large relative to proportion of disabled. In constrast, the bounds for the non-disabled, even in this case, are fairly informative. For example, we can bound the conditional probability of employment versus non-employment for the non-disabled to be at least 68.2% before the Great Recession and at least 65.2% afterwards. Moreover, the bounds are such that we cannot rule out the possibility of the employment gap between the non-disabled and disabled being zero. These results highlight the uncertainty created by allowing for a 10% misclassification rate.

We then combine additional assumptions with our assumption of a 10% maximum degree of misclassification in the data. These assumptions, while not innocuous, are transparent and can be easily ignored if the researcher does not find them credible. Nonetheless, we find that the assumption of orthogonal misclassification errors, in particular, has a lot of identifying power in the current context. Our level set and monotonicity restrictions have some, but not as much, identifying power. For example, adding the or-

[8] It is difficult to report a precise comparison from Gosling and Saloniki (2014) since they report separate estimates of the gap by gender, schooling, and age. That said, the estimated gaps are below roughly 0.60 only for young females with no education qualifications.

thogonality assumption, we can bound the conditional probability of employment versus non-employment for the disabled to be *at most* 64.7% before the Great Recession and *at most* 53.1% afterwards. The conditional probability of employment versus non-employment for the non-disabled is *at least* 74.1% before the Great Recession and *at least* 71.1% afterwards. Thus, the employment gap between the non-disabled and disabled is strictly positive and *at least* 9.4% (18.0%) in the pre (post) Great Recession period.

Imposing our level set and monotonicity restrictions without the orthogonality assumption yields similar results. However, combining all assumptions yields even great identifying power. Now, we can bound the conditional probability of employment versus non-employment for the disabled to be *at most* 63.1% before the Great Recession and *at most* 53.1% afterwards. The conditional probability of employment versus non-employment for the non-disabled is *at least* 78.3% before the Great Recession and *at least* 75.1% afterwards. Thus, the employment gap between the non-disabled and disabled is *at least* 15.2% (22.0%) in the pre (post) Great Recession period.

We obtain similar results when we analyze labor force participation and unemployment. However, with unemployment we are unable to sign the gap between the non-disabled and the disabled given the relatively low proportion of the sample that is disabled and unemployed (as opposed to out of the labor force). Nonetheless, we are able to exclude gaps of the magnitude estimated in the prior literature.

In sum, then, we reach three important conclusions. First, it is critical to account for misclassification when assessing how labor market status varies with disability status. Allowing for misclassification rates in line with prior evidence adds considerable uncertainty to estimated conditional probabilities and especially estimates of the employment and unemployment gaps. Second, the assumptions considered here are sufficient to tighten the bounds considerably on the conditional probabilities for the non-disabled, less so for the disabled. Nonetheless, we are able to learn a considerable amount about the disabled, and we are able to sign the employment gap. Finally, while not definitive, the change in the bounds in the period before and after the Great Recession is consistent with the labor market worsening over this span for the disabled. It is beyond the scope of this analysis to attribute these changes to the ADAAA versus a disproportionate adverse impact of the recession on the disabled. However, future work should investigate the state of the labor market for the disabled in the aftermath of the Great Recession and the effect of the ADAAA. In addition, future work should explore additional assumptions that might contribute to the identification of the conditional probabilities we analyze here.

Acknowledgements

The authors are greatful for comments from John Mullahy, Robin Sickles, Yonghong An, and conference participants at the Texas Econometrics Camp, February 22-23, 2020.

References

[1] Abowd, J.M. and A. Zellner (1985), "Estimating Gross Labor-Force Flows," *Journal of Business & Economic Statistics*, 3(3), 254-283

[2] Abraham, K.G., J.C. Haltiwanger, K. Sandusky, and J. Spletzer (2013), "Exploring Differences in Employment between Household and Establishment Data," *Journal of Labor Economics* 31, 2, S129-S172

[3] Acemoglu, D. and J.D. Angrist (2001), "Consequences of Employment Protection? The Case of the Americans with Disabilities Act," *Journal of Political Economy*, 109(5), 915-957

[4] Baker, M., M. Stabile, and C. Deri (2004), "What Do Self-Reported, Objective, Measures of Health Measure?" *Journal of Human Resources*, 39(4), 1067-1093

[5] Bound, J. and R. Burkhauser (1999), "Economic Analysis of Transfer Programs Targeted on People with Disabilities," in O. Ashenfelter and D. Card (eds.))*Handbook of Labor Economics*, Vol. 3C, New York: Elsevier Science, North-Holland.

[6] Burkhauser, R.V., M.C. Daly, A.J. Houtenville, and N. Nargis (2002), "Self-Reported Work-Limitation Data: What They Can and Cannot Tell Us," *Demography*, 39(3), 541-555

[7] Chua, T.C. and W.A. Fuller (1987), "A Model for Multinomial Response Error Applied to Labor Flows," *Journal of the American Statistical Association*, 82(397), 46-51

[8] DeLeire, T. (2000), "The Wage and Employment Effects of the Americans with Disabilities Act," *Journal of Human Resources*, 35(4), 693-715

[9] Feng, S. and Y. Hu (2013), "Misclassification Errors and the Underestimation of the US Unemployment Rate," *American Economic Review,* 103(2), 1054-1070

[10] Feng, S. Y. Hu, and J. Sun (2018), "On the Robustness of Alternative Unemployment Measures," *Economics Letters*, 166, 1-5

[11] Gundersen, C. and B. Kreider (2008), "Food Stamps and Food Insecurity: What Can Be Learned in the Presence of Nonclassical Measurement Error?" *Journal of Human Resources*, 43(2), 352-382

[12] Hale, T. (2001), "The Lack of a Disability Measure in Today's Current Population Survey," *Monthly Labor Review* 124, 38-40

[13] Hampel, F., E. Ronchetti, P. Rousseeuw, and W. Stahel (1986), *Robust Statistics*. New York: Wiley

[14] Horowitz, J.L. and C.F. Manski (1995), "Identification and Robustness with Contaminated and Corrupted Data," *Econometrica* 63, 281-302

[15] Hyslop, D. and W. Townsend (2017), "Employment Misclassification in Survey and Administrative Reports," *Economics Letters*, 115,19-23

[16] Imbens, G.W. and C.F. Manski (2004), "Confidence Intervals For Partially Identified Parameters," *Econometrica*, 72, 6, 1845-1857

[17] Kim, S. and S. Rhee (2018), "Measuring the Effects of Employment Protection Policies: Theory and Evidence from the Americans with Disabilities Act," *Labour Economics*, 54, 116-134

[18] Kreider, B. (1999), "Latent Work Disability and Reporting Bias," *Journal of Human Resources*, 34, 734-769.

[19] Kreider, B. and J.V. Pepper (2007), "Disability and Employment: Reevaluating the Evidence in Light of Reporting Errors," *Journal of the American Statistical Association,* June 2007, 102, 478

[20] Kreider, B. and J.V. Pepper (2008), "Inferring Disability Status from Corrupt Data," *Journal of Applied Economitrics,* 23, 329-349

[21] Kruse, D. and L. Schur (2003), "Employment of People with Disabilities Following the ADA," *Industrial Relations*, 42(1), 31-64

[22] Leroux, J., J.A. Rizzo, and R. Sickles (2012), "The Role of Self-Reporting Bias in Health, Mental Health and Labor Force Participation: A Descriptive Analysis," *Empirical Economics*, 43, 525-536

[23] Li, H., D.L. Millimet, and P. Roychowdhury (2019), "Measuring Economic Mobility in India Using Noisy Data: A Partial Identification Approach," IZA DP No. 12505

[24] Low, H. and L. Pistaferri (2019), "Disability Insurance: Error Rates and Gender Differences," NBER Working Paper No. 26513.

[25] Magnac, T. and J. Visser (1999), "Transition Models with Measurement Errors," *Review of Economics and Statistics*, 81(3), 466-474.

[26] Manski, C.F. and J.V. Pepper (2000), "Monotone Instrumental Variables: With an Application to the Returns to schooling," *Econometrica* 68, 4, 997-1010

[27] Manski, C.F. (2011), "Policy Analysis with Incredible Certitude," *Economic Journal*, 121, F261-F289.

[28] Millimet, D.L., H. Li, and P. Roychowdhury (2019), "Partial Identification of Economics Mobility: With an Application to the United States," *Journal of Business & Economic Statistics*, forthcoming, DOI: 10.1080/07350015.2019.1569527

[29] Poterba, J.M. and L.H. Summers (1986), "Reporting Errors and Labor Market Dynamics," *Econometrica* 54, 6, 1319-1338

[30] Poterba, J.M. and L.H. Summers (1995), "Unemployment Benefits and Labor Market Transitions: A Multinomial Logit Model with Errors in Classification," *Review of Economics and Statistics*, 77(2), 207-216

[31] Stern, S. (1989), "Measuring the Effect of Disability on Labor Force Participation," *Journal of Human Resources*, 24(3), 361-395

[32] Wilkins, R. (2004), "The Effects of Disability on Labour Force Status in Australia," *The Australian Economic Review*, 37(4), 359-382

Table 1. Summary Statistics.

	2004 Panel		2008 Panel		2014 Panel	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**
Labor Market Status						
Non-Employed (1 = Yes)	0.27	0.45	0.30	0.46	0.32	0.47
Out of the Labor Force (1 = Yes)	0.24	0.43	0.25	0.43	0.27	0.45
Unemployed (1 = Yes, 0 = Employed)	0.04	0.20	0.07	0.26	0.06	0.24
Disability (1 = Yes)	0.14	0.35	0.16	0.36	0.16	0.36
Household Size						
Number of Adults	2.86	1.55	2.88	1.60	2.75	1.59
Number of Children Less Than 18	0.82	1.16	0.78	1.16	0.73	1.15
Age						
25-33 (1 = Yes)	0.21	0.41	0.21	0.41	0.32	0.47
34-42 (1 = Yes)	0.23	0.42	0.25	0.43	0.12	0.32
43-51 (1 = Yes)	0.21	0.41	0.15	0.36	0.13	0.33
52-60 (1 = Yes)	0.18	0.38	0.16	0.37	0.17	0.37
61-69 (1 = Yes)	0.17	0.37	0.23	0.42	0.26	0.44
Family Non-Labor Income (Monthly $, Per Equivelent Adult)						
Less than 0.1 (1 = Yes)	0.21	0.41	0.19	0.39	0.20	0.40
0.1 - 10 (1 = Yes)	0.24	0.43	0.20	0.40	0.20	0.40
10 - 200 (1 = Yes)	0.24	0.43	0.23	0.42	0.20	0.40
200 - 725 (1 = Yes)	0.19	0.39	0.22	0.41	0.22	0.42
More than 725 (1 = Yes)	0.12	0.33	0.16	0.36	0.18	0.38
N	61,171		51,429		40,991	

Notes: Samples from the Survey of Income and Program Participation (SIPP). Data for the 2004 Panel are from January 2004. Data for the 2008 Panel are from August 2009. Data for the 2014 Panel are from October 2013.

Table 2. Conditional Probabilities of Employment & Non-Employment: Misclassification Assumptions.

	2004 Panel			2008 Panel			2014 Panel	
I. No Misclassification								
	Employed (Y=0)	**Non-Emp. (Y=1)**		**Employed (Y=0)**	**Non-Emp. (Y=1)**		**Employed (Y=0)**	**Non-Emp. (Y=1)**
Non-Disabled	[0.799,0.799]	[0.201,0.201]	**Non-Disabled**	[0.777,0.777]	[0.223,0.223]	**Non-Disabled**	[0.770,0.770]	[0.230,0.230]
(D=0)	(0.796,0.801)	(0.199,0.204)	**(D=0)**	(0.774,0.781)	(0.219,0.226)	**(D=0)**	(0.766,0.774)	(0.226,0.234)
Disabled	[0.287,0.287]	[0.713,0.713]	**Disabled**	[0.271,0.271]	[0.729,0.729]	**Disabled**	[0.208,0.208]	[0.792,0.792]
(D=1)	(0.279,0.295)	(0.705,0.721)	**(D=1)**	(0.263,0.279)	(0.721,0.737)	**(D=1)**	(0.200,0.216)	(0.784,0.800)
II. Misclassification (Q = 0.10)								
	Employed (Y=0)	**Non-Emp. (Y=1)**		**Employed (Y=0)**	**Non-Emp. (Y=1)**		**Employed (Y=0)**	**Non-Emp. (Y=1)**
Non-Disabled	[0.682,0.915]	[0.085,0.318]	**Non-Disabled**	[0.659,0.896]	[0.104,0.341]	**Non-Disabled**	[0.652,0.888]	[0.112,0.348]
(D=0)	(0.680,0.917)	(0.083,0.320)	**(D=0)**	(0.656,0.898)	(0.102,0.344)	**(D=0)**	(0.649,0.891)	(0.109,0.351)
Disabled	[0.000,1.000]	[0.000,1.000]	**Disabled**	[0.000,0.915]	[0.085,1.000]	**Disabled**	[0.000,0.853]	[0.147,1.000]
(D=1)	(0.000,1.000)	(0.000,1.000)	**(D=1)**	(0.000,0.926)	(0.074,1.000)	**(D=1)**	(0.000,0.865)	(0.135,1.000)
III. Misclassification + Orthogonality (Q = 0.10)								
	Employed (Y=0)	**Non-Emp. (Y=1)**		**Employed (Y=0)**	**Non-Emp. (Y=1)**		**Employed (Y=0)**	**Non-Emp. (Y=1)**
Non-Disabled	[0.741,0.857]	[0.143,0.259]	**Non-Disabled**	[0.718,0.836]	[0.164,0.282]	**Non-Disabled**	[0.711,0.829]	[0.171,0.289]
(D=0)	(0.738,0.859)	(0.141,0.262)	**(D=0)**	(0.716,0.839)	(0.161,0.284)	**(D=0)**	(0.708,0.832)	(0.168,0.292)
Disabled	[0.000,0.647]	[0.353,1.000]	**Disabled**	[0.000,0.593]	[0.407,1.000]	**Disabled**	[0.000,0.531]	[0.469,1.000]
(D=1)	(0.000,0.655)	(0.345,1.000)	**(D=1)**	(0.000,0.601)	(0.399,1.000)	**(D=1)**	(0.000,0.538)	(0.462,1.000)

Notes: Point estimates for bounds provided in brackets obtained using 50 subsamples of size N/2 for bias correction. 90% Imbens-Manski confidence intervals for the bounds provided in parentheses obtained using 200 subsamples of size N/2. See text for further details.

Table 3. Conditional Probabilities of Employment & Non-Employment: Level Set + Monotonicity Restrictions.

	2004 Panel			**2008 Panel**			**2014 Panel**	
I. No Orthogonality								
A. Independent Misclassification + Level Set Restrictions (Q = 0.10)								
	Employed (Y=0)	**Non-Emp. (Y=1)**		**Employed (Y=0)**	**Non-Emp. (Y=1)**		**Employed (Y=0)**	**Non-Emp. (Y=1)**
Non-Disabled	[0.727,0.874]	[0.126,0.273]	**Non-Disabled**	[0.710,0.845]	[0.155,0.290]	**Non-Disabled**	[0.740,0.824]	[0.176,0.260]
(D=0)	(0.724,0.877)	(0.123,0.276)	**(D=0)**	(0.706,0.849)	(0.151,0.294)	**(D=0)**	(0.730,0.840)	(0.160,0.270)
Disabled	[0.000,0.743]	[0.257,1.000]	**Disabled**	[0.000,0.735]	[0.265,1.000]	**Disabled**	[0.000,0.727]	[0.273,1.000]
(D=1)	(0.000,0.748)	(0.252,1.000)	**(D=1)**	(0.000,0.740)	(0.260,1.000)	**(D=1)**	(0.000,0.732)	(0.268,1.000)
B. Independent Misclassification + Level Set, Monotoncity Restrictions (Q = 0.10)								
	Employed (Y=0)	**Non-Emp. (Y=1)**		**Employed (Y=0)**	**Non-Emp. (Y=1)**		**Employed (Y=0)**	**Non-Emp. (Y=1)**
Non-Disabled	[0.746,0.824]	[0.176,0.254]	**Non-Disabled**	[0.735,0.791]	[0.209,0.265]	**Non-Disabled**	[0.740,0.821]	[0.179,0.260]
(D=0)	(0.742,0.831)	(0.169,0.258)	**(D=0)**	(0.731,0.802)	(0.198,0.269)	**(D=0)**	(0.730,0.828)	(0.172,0.270)
Disabled	[0.000,0.743]	[0.257,1.000]	**Disabled**	[0.000,0.735]	[0.265,1.000]	**Disabled**	[0.000,0.727]	[0.273,1.000]
(D=1)	(0.000,0.748)	(0.252,1.000)	**(D=1)**	(0.000,0.740)	(0.260,1.000)	**(D=1)**	(0.000,0.732)	(0.268,1.000)
II. With Orthogonality								
A. Independent Misclassification + Level Set Restrictions (Q = 0.10)								
	Employed (Y=0)	**Non-Emp. (Y=1)**		**Employed (Y=0)**	**Non-Emp. (Y=1)**		**Employed (Y=0)**	**Non-Emp. (Y=1)**
Non-Disabled	[0.742,0.831]	[0.169,0.258]	**Non-Disabled**	[0.718,0.802]	[0.198,0.282]	**Non-Disabled**	[0.719,0.810]	[0.190,0.281]
(D=0)	(0.739,0.833)	(0.167,0.261)	**(D=0)**	(0.716,0.805)	(0.195,0.284)	**(D=0)**	(0.716,0.813)	(0.187,0.284)
Disabled	[0.006,0.642]	[0.358,0.994]	**Disabled**	[0.004,0.593]	[0.407,0.996]	**Disabled**	[0.000,0.531]	[0.469,1.000]
(D=1)	(0.001,0.646)	(0.354,0.999)	**(D=1)**	(0.000,0.601)	(0.399,1.000)	**(D=1)**	(0.000,0.538)	(0.462,1.000)
B. Independent Misclassification + Level Set, Monotoncity Restrictions (Q = 0.10)								
	Employed (Y=0)	**Non-Emp. (Y=1)**		**Employed (Y=0)**	**Non-Emp. (Y=1)**		**Employed (Y=0)**	**Non-Emp. (Y=1)**
Non-Disabled	[0.783,0.792]	[0.208,0.217]	**Non-Disabled**	[0.745,0.755]	[0.245,0.255]	**Non-Disabled**	[0.751,0.770]	[0.783,0.792]
(D=0)	(0.776,0.797)	(0.203,0.224)	**(D=0)**	(0.740,0.769)	(0.231,0.260)	**(D=0)**	(0.741,0.776)	(0.776,0.797)
Disabled	[0.068,0.631]	[0.369,0.932]	**Disabled**	[0.074,0.593]	[0.407,0.926]	**Disabled**	[0.000,0.531]	[0.068,0.631]
(D=1)	(0.048,0.638)	(0.362,0.952)	**(D=1)**	(0.052,0.601)	(0.399,0.948)	**(D=1)**	(0.000,0.538)	(0.462,1.000)

Notes: Point estimates for bounds provided in brackets obtained using 50 subsamples of size N/2 for bias correction. 90% Imbens-Manski confidence intervals for the bounds provided in parentheses obtained using 200 subsamples of size N/2. Level set restrictions based on family non-labor income. Monotonicity restrictions based on individual age. See text for further details.

Table 4. Conditional Probabilities of Labor Force Participation: Misclassification Assumptions.

	2004 Panel			2008 Panel			2014 Panel	
I. No Misclassification								
	LF	**OLF**		**LF**	**OLF**		**LF**	**OLF**
	(Y=0)	**(Y=1)**		**(Y=0)**	**(Y=1)**		**(Y=0)**	**(Y=1)**
Non-Disabled	[0.833,0.833]	[0.167,0.167]	**Non-Disabled**	[0.835,0.835]	[0.165,0.165]	**Non-Disabled**	[0.810,0.810]	[0.190,0.190]
(D=0)	(0.830,0.836)	(0.164,0.170)	**(D=0)**	(0.832,0.837)	(0.163,0.168)	**(D=0)**	(0.807,0.813)	(0.187,0.193)
Disabled	[0.312,0.312]	[0.688,0.688]	**Disabled**	[0.315,0.315]	[0.685,0.685]	**Disabled**	[0.273,0.273]	[0.727,0.727]
(D=1)	(0.304,0.321)	(0.679,0.696)	**(D=1)**	(0.306,0.323)	(0.677,0.694)	**(D=1)**	(0.265,0.281)	(0.719,0.735)
II. Misclassification (Q = 0.10)								
	LF	**OLF**		**LF**	**OLF**		**LF**	**OLF**
	(Y=0)	**(Y=1)**		**(Y=0)**	**(Y=1)**		**(Y=0)**	**(Y=1)**
Non-Disabled	[0.717,0.949]	[0.051,0.283]	**Non-Disabled**	[0.716,0.953]	[0.047,0.284]	**Non-Disabled**	[0.692,0.928]	[0.072,0.308]
(D=0)	(0.715,0.951)	(0.049,0.285)	**(D=0)**	(0.714,0.955)	(0.045,0.286)	**(D=0)**	(0.689,0.931)	(0.069,0.311)
Disabled	[0.000,1.000]	[0.000,1.000]	**Disabled**	[0.000,0.958]	[0.042,1.000]	**Disabled**	[0.000,0.918]	[0.082,1.000]
(D=1)	(0.000,1.000)	(0.000,1.000)	**(D=1)**	(0.000,0.969)	(0.031,1.000)	**(D=1)**	(0.000,0.930)	(0.070,1.000)
III. Misclassification + Orthogonality (Q = 0.10)								
	LF	**OLF**		**LF**	**OLF**		**LF**	**OLF**
	(Y=0)	**(Y=1)**		**(Y=0)**	**(Y=1)**		**(Y=0)**	**(Y=1)**
Non-Disabled	[0.775,0.891]	[0.109,0.225]	**Non-Disabled**	[0.775,0.894]	[0.106,0.225]	**Non-Disabled**	[0.751,0.869]	[0.131,0.249]
(D=0)	(0.773,0.893)	(0.107,0.227)	**(D=0)**	(0.773,0.896)	(0.104,0.227)	**(D=0)**	(0.748,0.872)	(0.128,0.252)
Disabled	[0.000,0.673]	[0.327,1.000]	**Disabled**	[0.000,0.636]	[0.364,1.000]	**Disabled**	[0.000,0.595]	[0.405,1.000]
(D=1)	(0.000,0.681)	(0.319,1.000)	**(D=1)**	(0.000,0.644)	(0.356,1.000)	**(D=1)**	(0.000,0.603)	(0.397,1.000)

Notes: LF = labor force participant. OLF = out of labor force. Point estimates for bounds provided in brackets obtained using 50 subsamples of size N/2 for bias correction. 90% Imbens-Manski confidence intervals for the bounds provided in parentheses obtained using 200 subsamples of size N/2. See text for further details.

Table 5. Conditional Probabilities of Labor Force Participation: Level Set + Monotonicity Restrictions.

2004 Panel			2008 Panel			2014 Panel		
I. No Orthogonality								
A. Independent Misclassification + Level Set Restrictions (Q = 0.10)								
	LF	**OLF**		**LF**	**OLF**		**LF**	**OLF**
	(Y=0)	**(Y=1)**		**(Y=0)**	**(Y=1)**		**(Y=0)**	**(Y=1)**
Non-Disabled	[0.760,0.923]	[0.077,0.240]	**Non-Disabled**	[0.770,0.927]	[0.073,0.230]	**Non-Disabled**	[0.749,0.878]	[0.122,0.251]
(D=0)	(0.757,0.926)	(0.074,0.243)	**(D=0)**	(0.767,0.930)	(0.070,0.233)	**(D=0)**	(0.741,0.895)	(0.105,0.259)
Disabled	[0.000,0.752]	[0.248,1.000]	**Disabled**	[0.000,0.756]	[0.244,1.000]	**Disabled**	[0.000,0.758]	[0.242,1.000]
(D=1)	(0.000,0.758)	(0.242,1.000)	**(D=1)**	(0.000,0.761)	(0.239,1.000)	**(D=1)**	(0.000,0.763)	(0.237,1.000)
B. Independent Misclassification + Level Set, Monotoncity Restrictions (Q = 0.10)								
	LF	**OLF**		**LF**	**OLF**		**LF**	**OLF**
	(Y=0)	**(Y=1)**		**(Y=0)**	**(Y=1)**		**(Y=0)**	**(Y=1)**
Non-Disabled	[0.768,0.890]	[0.110,0.232]	**Non-Disabled**	[0.770,0.889]	[0.111,0.230]	**Non-Disabled**	[0.749,0.878]	[0.122,0.251]
(D=0)	(0.764,0.895)	(0.105,0.236)	**(D=0)**	(0.767,0.895)	(0.105,0.233)	**(D=0)**	(0.741,0.885)	(0.115,0.259)
Disabled	[0.000,0.752]	[0.248,1.000]	**Disabled**	[0.000,0.756]	[0.244,1.000]	**Disabled**	[0.000,0.758]	[0.242,1.000]
(D=1)	(0.000,0.758)	(0.242,1.000)	**(D=1)**	(0.000,0.761)	(0.239,1.000)	**(D=1)**	(0.000,0.763)	(0.237,1.000)
II. With Orthogonality								
A. Independent Misclassification + Level Set Restrictions (Q = 0.10)								
	LF	**OLF**		**LF**	**OLF**		**LF**	**OLF**
	(Y=0)	**(Y=1)**		**(Y=0)**	**(Y=1)**		**(Y=0)**	**(Y=1)**
Non-Disabled	[0.777,0.860]	[0.140,0.223]	**Non-Disabled**	[0.775,0.864]	[0.136,0.225]	**Non-Disabled**	[0.751,0.851]	[0.149,0.249]
(D=0)	(0.775,0.864)	(0.136,0.225)	**(D=0)**	(0.773,0.867)	(0.133,0.227)	**(D=0)**	(0.748,0.854)	(0.146,0.252)
Disabled	[0.018,0.651]	[0.349,0.982]	**Disabled**	[0.031,0.636]	[0.364,0.969]	**Disabled**	[0.016,0.591]	[0.409,0.984]
(D=1)	(0.012,0.656)	(0.344,0.988)	**(D=1)**	(0.025,0.644)	(0.356,0.975)	**(D=1)**	(0.009,0.603)	(0.397,0.991)
B. Independent Misclassification + Level Set, Monotoncity Restrictions (Q = 0.10)								
	LF	**OLF**		**LF**	**OLF**		**LF**	**OLF**
	(Y=0)	**(Y=1)**		**(Y=0)**	**(Y=1)**		**(Y=0)**	**(Y=1)**
Non-Disabled	[0.800,0.834]	[0.166,0.200]	**Non-Disabled**	[0.800,0.835]	[0.165,0.200]	**Non-Disabled**	[0.767,0.827]	[0.173,0.233]
(D=0)	(0.796,0.840)	(0.160,0.204)	**(D=0)**	(0.796,0.841)	(0.159,0.204)	**(D=0)**	(0.759,0.834)	(0.166,0.241)
Disabled	[0.088,0.646]	[0.354,0.912]	**Disabled**	[0.117,0.636]	[0.364,0.883]	**Disabled**	[0.049,0.591]	[0.409,0.951]
(D=1)	(0.069,0.653)	(0.347,0.931)	**(D=1)**	(0.095,0.644)	(0.356,0.905)	**(D=1)**	(0.029,0.603)	(0.397,0.971)

Notes: LF = labor force participant. OLF = out of labor force. Point estimates for bounds provided in brackets obtained using 50 subsamples of size N/2 for bias correction. 90% Imbens-Manski confidence intervals for the bounds provided in parentheses obtained using 200 subsamples of size N/2. Level set restrictions based on family non-labor income. Monotonicity restrictions based on individual age. See text for further details.

Table 6. Conditional Probabilities of Employment & Unemployment: Misclassification Assumptions.

2004 Panel			2008 Panel			2014 Panel		
I. No Misclassification								
	Employed (Y=0)	**Unemp. (Y=1)**		**Employed (Y=0)**	**Unemp. (Y=1)**		**Employed (Y=0)**	**Unemp. (Y=1)**
Non-Disabled	[0.958,0.958]	[0.042,0.042]	**Non-Disabled**	[0.931,0.931]	[0.069,0.069]	**Non-Disabled**	[0.950,0.950]	[0.050,0.050]
(D=0)	(0.957,0.960)	(0.040,0.043)	**(D=0)**	(0.929,0.934)	(0.066,0.071)	**(D=0)**	(0.949,0.952)	(0.048,0.051)
Disabled	[0.919,0.919]	[0.081,0.081]	**Disabled**	[0.862,0.862]	[0.138,0.138]	**Disabled**	[0.763,0.763]	[0.237,0.237]
(D=1)	(0.910,0.927)	(0.073,0.090)	**(D=1)**	(0.851,0.873)	(0.127,0.149)	**(D=1)**	(0.747,0.779)	(0.221,0.253)
II. Misclassification (Q = 0.10)								
	Employed (Y=0)	**Unemp. (Y=1)**		**Employed (Y=0)**	**Unemp. (Y=1)**		**Employed (Y=0)**	**Unemp. (Y=1)**
Non-Disabled	[0.852,1.000]	[0.000,0.148]	**Non-Disabled**	[0.824,1.000]	[0.000,0.176]	**Non-Disabled**	[0.844,1.000]	[0.000,0.156]
(D=0)	(0.851,1.000)	(0.000,0.149)	**(D=0)**	(0.823,1.000)	(0.000,0.177)	**(D=0)**	(0.843,1.000)	(0.000,0.157)
Disabled	[0.000,1.000]	[0.000,1.000]	**Disabled**	[0.000,1.000]	[0.000,1.000]	**Disabled**	[0.000,1.000]	[0.000,1.000]
(D=1)	(0.000,1.000)	(0.000,1.000)	**(D=1)**	(0.000,1.000)	(0.000,1.000)	**(D=1)**	(0.000,1.000)	(0.000,1.000)
III. Misclassification + Orthogonality (Q = 0.10)								
	Employed (Y=0)	**Unemp. (Y=1)**		**Employed (Y=0)**	**Unemp. (Y=1)**		**Employed (Y=0)**	**Unemp. (Y=1)**
Non-Disabled	[0.905,1.000]	[0.000,0.095]	**Non-Disabled**	[0.878,0.985]	[0.015,0.122]	**Non-Disabled**	[0.897,1.000]	[0.000,0.103]
(D=0)	(0.904,1.000)	(0.000,0.096)	**(D=0)**	(0.876,0.987)	(0.013,0.124)	**(D=0)**	(0.896,1.000)	(0.000,0.104)
Disabled	[0.041,1.000]	[0.000,0.959]	**Disabled**	[0.091,1.000]	[0.000,0.909]	**Disabled**	[0.000,1.000]	[0.000,1.000]
(D=1)	(0.020,1.000)	(0.000,0.980)	**(D=1)**	(0.071,1.000)	(0.000,0.929)	**(D=1)**	(0.000,1.000)	(0.000,1.000)

Notes: Sample restricted to individuals in the labor force. Point estimates for bounds provided in brackets obtained using 50 subsamples of size N/2 for bias correction. 90% Imbens-Manski confidence intervals for the bounds provided in parentheses obtained using 200 subsamples of size N/2. See text for further details.

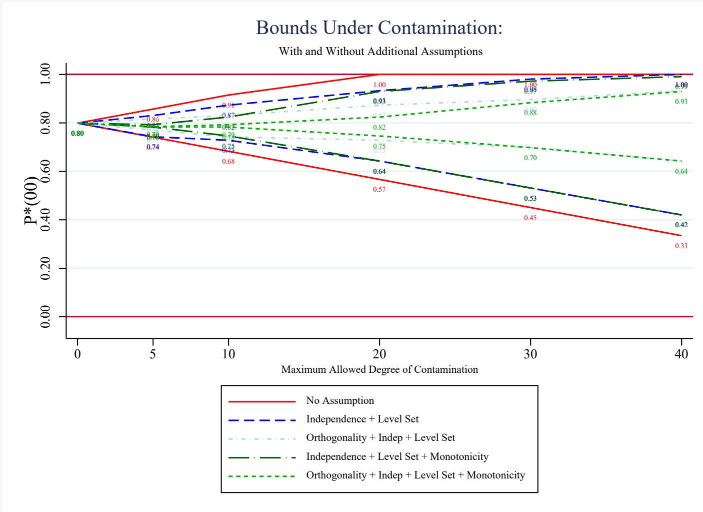
Table 7. Conditional Probabilities of Employment & Unemployment: Level Set + Monotonicity Restrictions.

2004 Panel			2008 Panel			2014 Panel		
I. No Orthogonality								
A. Independent Misclassification + Level Set Restrictions (Q = 0.10)								
	Employed (Y=0)	**Unemp. (Y=1)**		**Employed (Y=0)**	**Unemp. (Y=1)**		**Employed (Y=0)**	**Unemp. (Y=1)**
Non-Disabled	[0.871,1.000]	[0.000,0.129]	**Non-Disabled**	[0.853,0.983]	[0.017,0.147]	**Non-Disabled**	[0.865,1.000]	[0.000,0.135]
(D=0)	(0.869,1.000)	(0.000,0.131)	**(D=0)**	(0.851,0.985)	(0.015,0.149)	**(D=0)**	(0.863,1.000)	(0.000,0.137)
Disabled	[0.000,1.000]	[0.000,1.000]	**Disabled**	[0.028,1.000]	[0.000,0.972]	**Disabled**	[0.000,1.000]	[0.000,1.000]
(D=1)	(0.000,1.000)	(0.000,1.000)	**(D=1)**	(0.017,1.000)	(0.000,0.983)	**(D=1)**	(0.000,1.000)	(0.000,1.000)
B. Independent Misclassification + Level Set, Monotoncity Restrictions (Q = 0.10)								
	Employed (Y=0)	**Unemp. (Y=1)**		**Employed (Y=0)**	**Unemp. (Y=1)**		**Employed (Y=0)**	**Unemp. (Y=1)**
Non-Disabled	[0.874,0.986]	[0.014,0.126]	**Non-Disabled**	[0.859,0.962]	[0.038,0.141]	**Non-Disabled**	[0.872,0.993]	[0.007,0.128]
(D=0)	(0.872,0.990)	(0.010,0.128)	**(D=0)**	(0.857,0.968)	(0.032,0.143)	**(D=0)**	(0.870,0.997)	(0.003,0.130)
Disabled	[0.120,1.000]	[0.000,0.880]	**Disabled**	[0.106,1.000]	[0.000,0.894]	**Disabled**	[0.000,1.000]	[0.000,1.000]
(D=1)	(0.073,1.000)	(0.000,0.927)	**(D=1)**	(0.079,1.000)	(0.000,0.921)	**(D=1)**	(0.000,1.000)	(0.000,1.000)
II. With Orthogonality								
A. Independent Misclassification + Level Set Restrictions (Q = 0.10)								
	Employed (Y=0)	**Unemp. (Y=1)**		**Employed (Y=0)**	**Unemp. (Y=1)**		**Employed (Y=0)**	**Unemp. (Y=1)**
Non-Disabled	[0.923,0.988]	[0.012,0.077]	**Non-Disabled**	[0.881,0.972]	[0.028,0.119]	**Non-Disabled**	[0.917,0.995]	[0.005,0.083]
(D=0)	(0.922,0.990)	(0.010,0.078)	**(D=0)**	(0.876,0.974)	(0.026,0.124)	**(D=0)**	(0.915,0.997)	(0.003,0.085)
Disabled	[0.199,1.000]	[0.000,0.801]	**Disabled**	[0.182,1.000]	[0.000,0.818]	**Disabled**	[0.112,1.000]	[0.000,0.888]
(D=1)	(0.186,1.000)	(0.000,0.814)	**(D=1)**	(0.172,1.000)	(0.000,0.828)	**(D=1)**	(0.100,1.000)	(0.000,0.900)
B. Independent Misclassification + Level Set, Monotoncity Restrictions (Q = 0.10)								
	Employed (Y=0)	**Unemp. (Y=1)**		**Employed (Y=0)**	**Unemp. (Y=1)**		**Employed (Y=0)**	**Unemp. (Y=1)**
Non-Disabled	[0.926,0.970]	[0.030,0.074]	**Non-Disabled**	[0.910,0.944]	[0.056,0.090]	**Non-Disabled**	[0.925,0.964]	[0.036,0.075]
(D=0)	(0.924,0.975)	(0.025,0.076)	**(D=0)**	(0.906,0.950)	(0.050,0.094)	**(D=0)**	(0.922,0.969)	(0.031,0.078)
Disabled	[0.529,1.000]	[0.000,0.471]	**Disabled**	[0.465,1.000]	[0.000,0.535]	**Disabled**	[0.323,1.000]	[0.000,0.677]
(D=1)	(0.496,1.000)	(0.000,0.504)	**(D=1)**	(0.437,1.000)	(0.000,0.563)	**(D=1)**	(0.280,1.000)	(0.000,0.720)

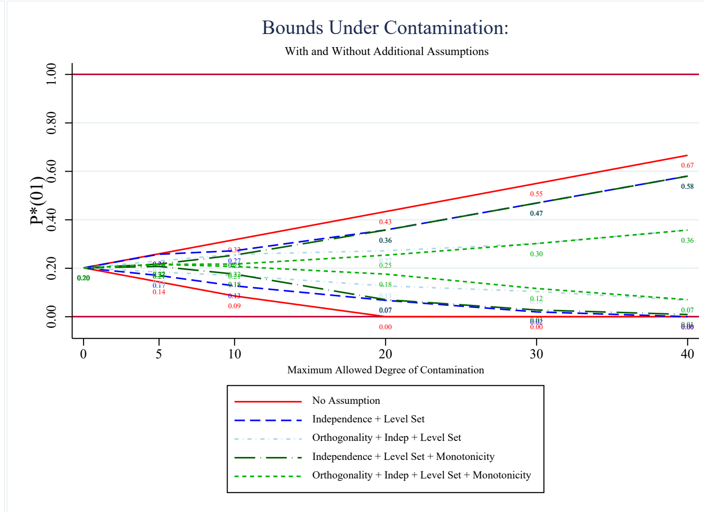
Notes: Sample restricted to individuals in the labor force. Point estimates for bounds provided in brackets obtained using 50 subsamples of size N/2 for bias correction. 90% Imbens-Manski confidence intervals for the bounds provided in parentheses obtained using 200 subsamples of size N/2. Level set restrictions based on family non-labor income. Monotonicity restrictions based on individual age. See text for further details.

Supplemental Appendix

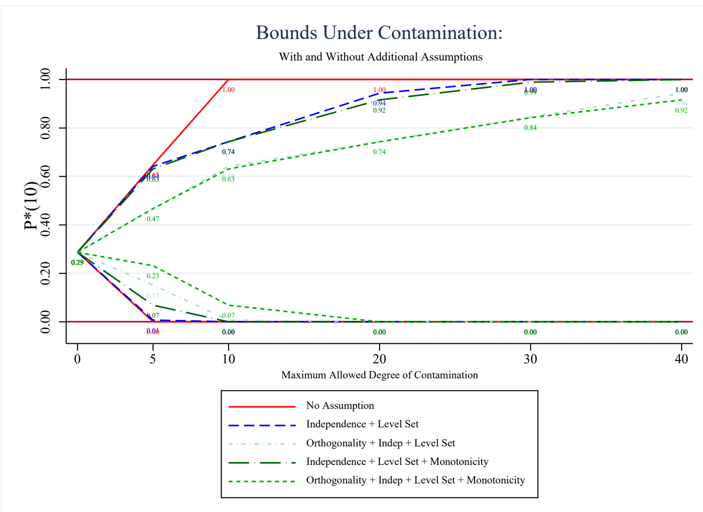
Bounding the Joint Distribution of Disability and Employment with Contaminated Data



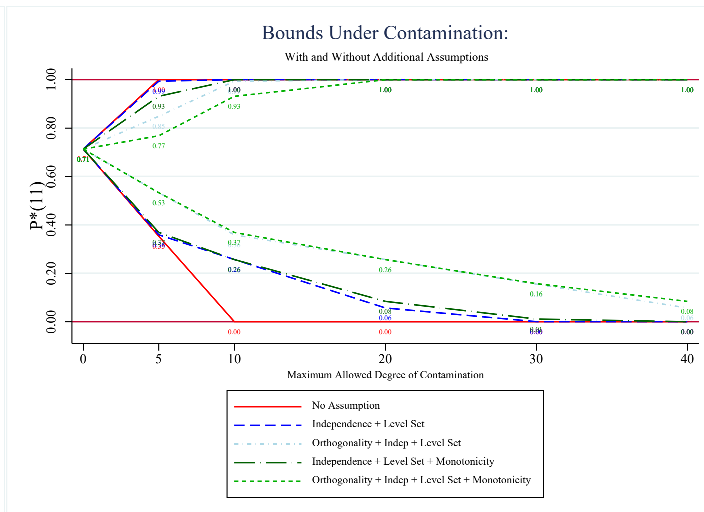
(A)



(B)



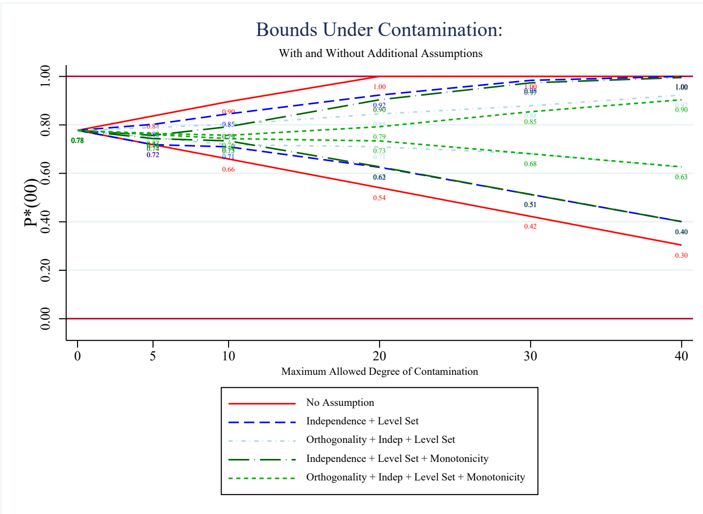
(C)

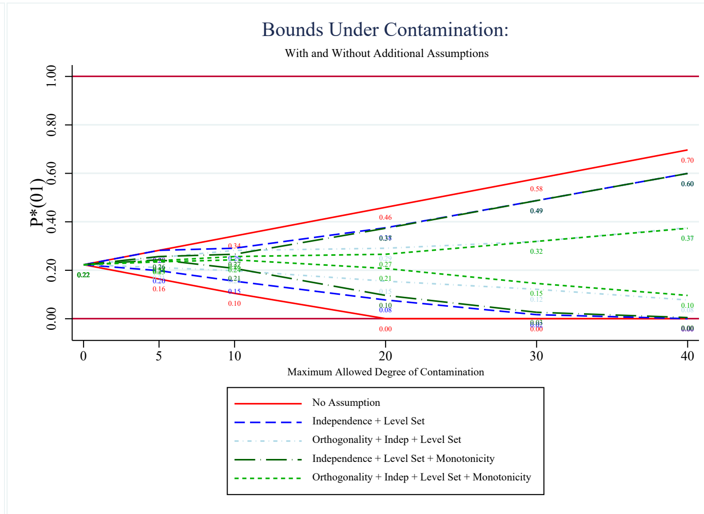


(D)

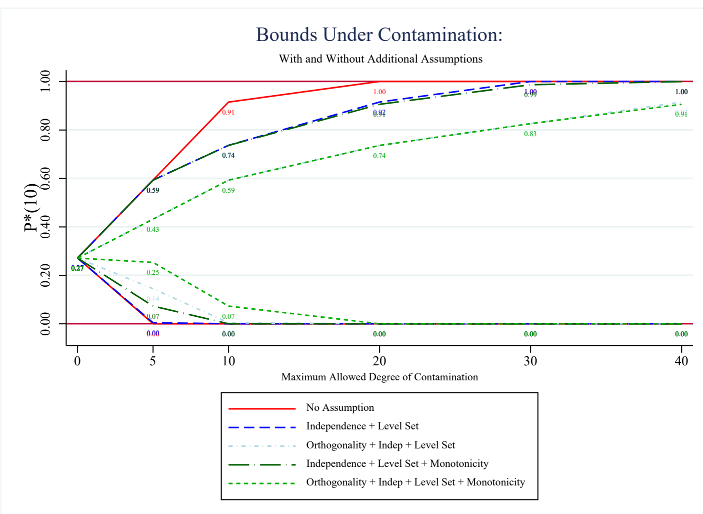
Figure A1. Conditional Probabilities of Employment & Non-Employment Under Various Assumptions and Maximum Misclassification Rates: 2004 Panel.

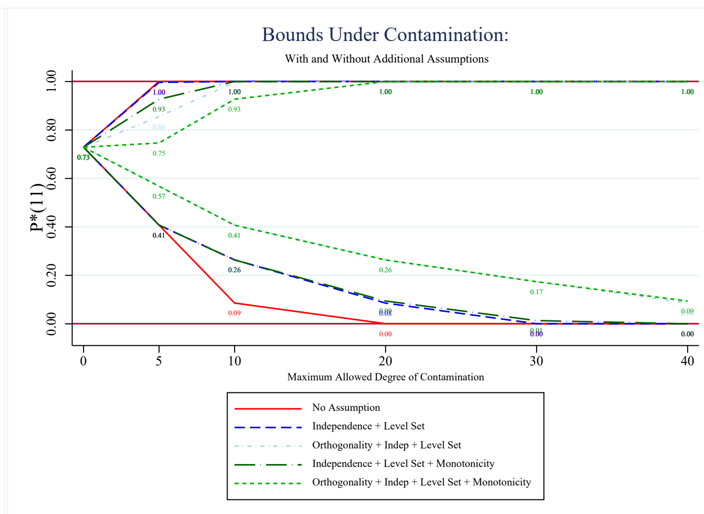
Notes: P*(00) = Pr(Emp | Non-disabled), P*(01) = Pr(Non-Emp | Non-disabled), P*(10) = Pr(Emp | Disabled), P*(11) = Pr(Non-Emp | Disabled). Point estimates for bounds obtained using 50 subsamples of size N/2 for bias correction. Level set restrictions based on family non-labor income. Monotonicity restrictions based on individual age. See text for further details.





(A) **(B)**

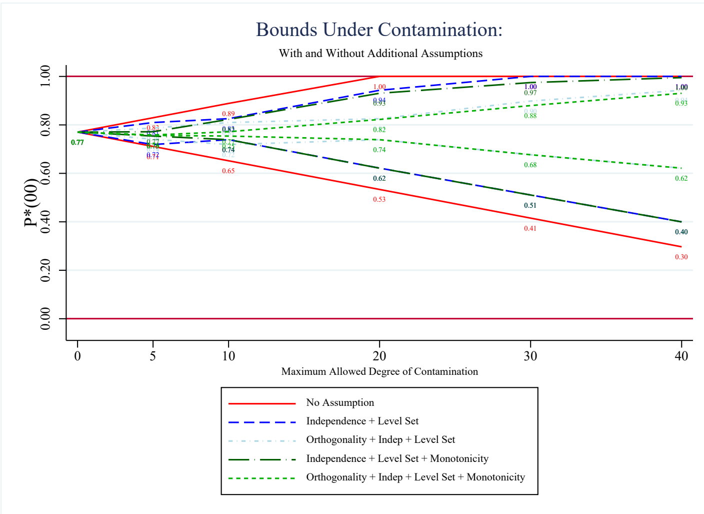




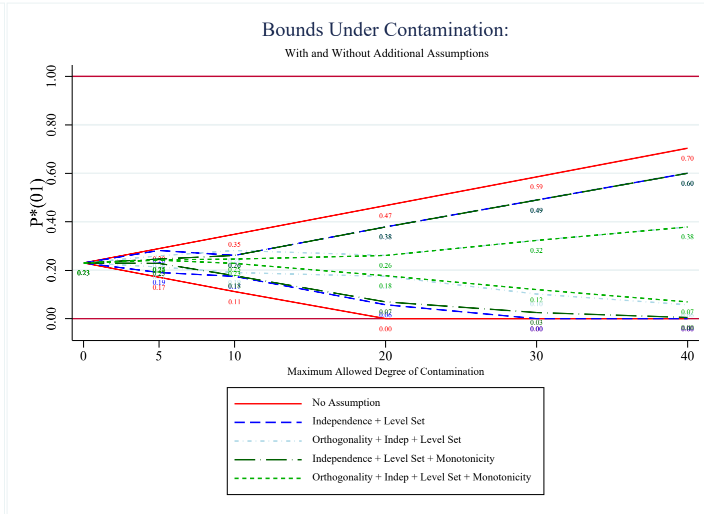
(C) **(D)**

Figure A2. Conditional Probabilities of Employment & Non-Employment Under Various Assumptions and Maximum Misclassification Rates: 2008 Panel.

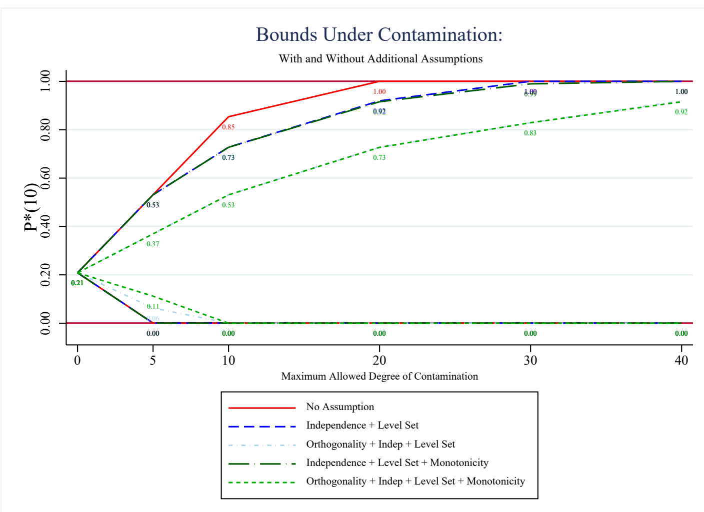
Notes: P*(00) = Pr(Emp | Non-disabled), P*(01) = Pr(Non-Emp | Non-disabled), P*(10) = Pr(Emp | Disabled), P*(11) = Pr(Non-Emp | Disabled). Point estimates for bounds obtained using 50 subsamples of size N/2 for bias correction. Level set restrictions based on family non-labor income. Monotonicity restrictions based on individual age. See text for further details.



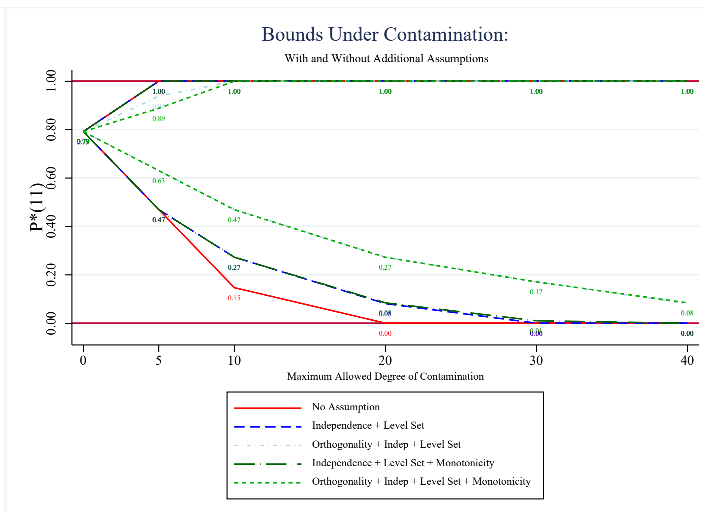
(A)



(B)



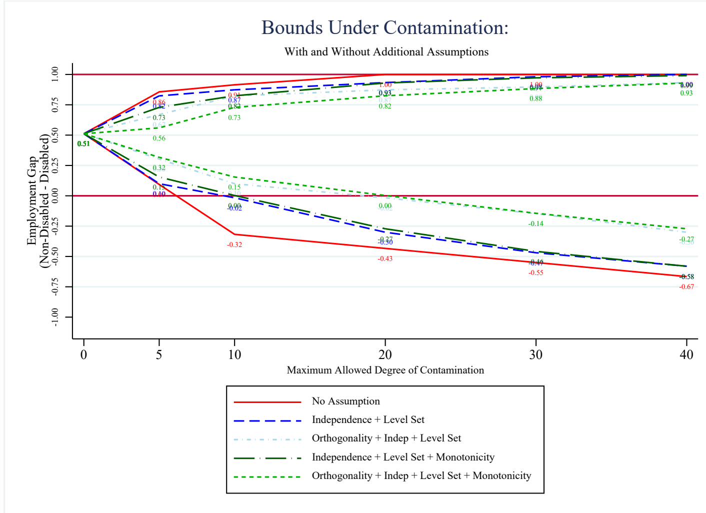
(C)



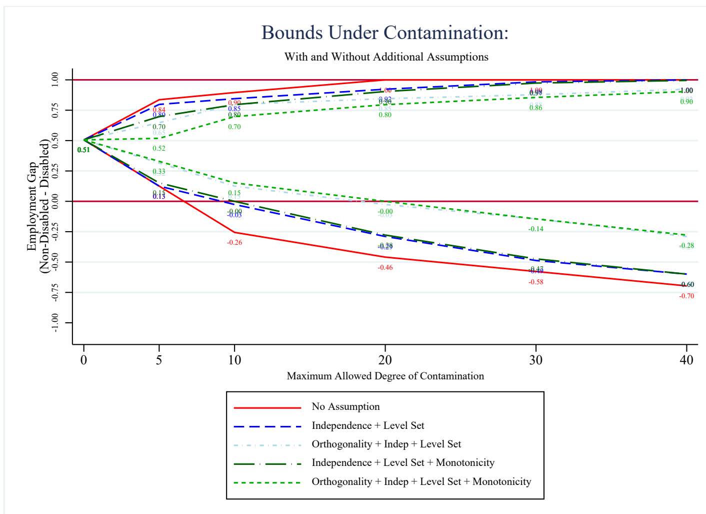
(D)

Figure A3. Conditional Probabilities of Employment & Non-Employment Under Various Assumptions and Maximum Misclassification Rates: 2014 Panel.

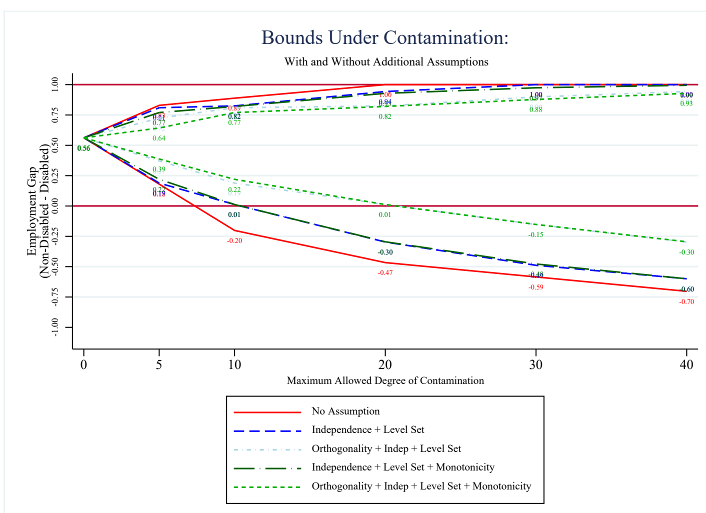
Notes: P*(00) = Pr(Emp | Non-disabled), P*(01) = Pr(Non-Emp | Non-disabled), P*(10) = Pr(Emp | Disabled), P*(11) = Pr(Non-Emp | Disabled). Point estimates for bounds obtained using 50 subsamples of size N/2 for bias correction. Level set restrictions based on family non-labor income. Monotonicity restrictions based on individual age. See text for further details.



(A) 2004 Panel

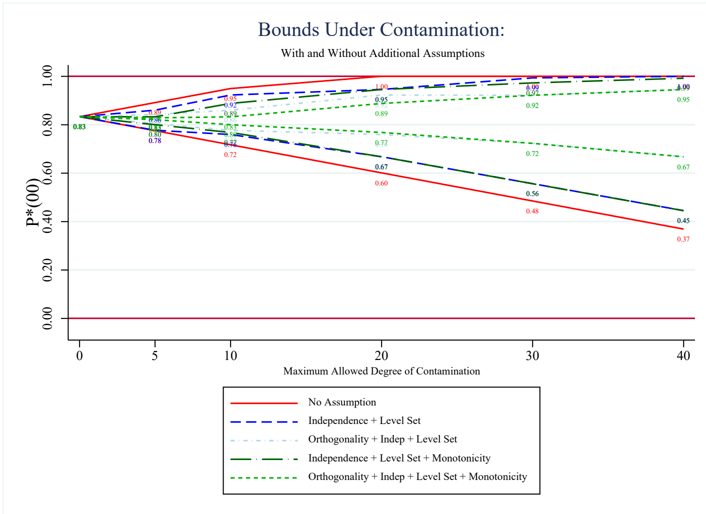


(B) 2008 Panel

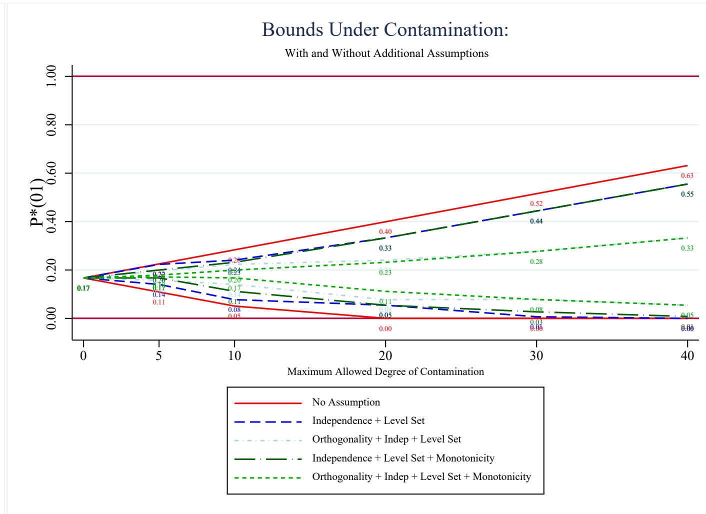


(C) 2014 Panel

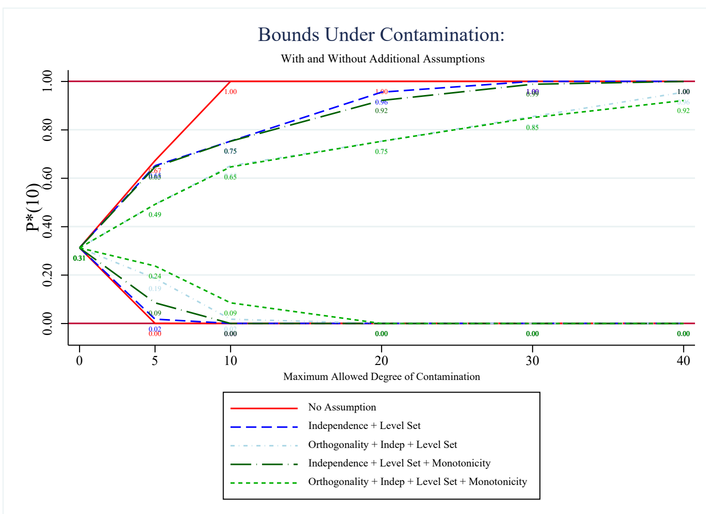
Figure A4. Employment Gaps Under Various Assumptions and Maximum Misclassification Rates by Year.
Notes: Employment gap is defined as the difference in the probability of being employed versus non-employed between the non-disabled and the disabled. Point estimates for bounds obtained using 50 subsamples of size N/2 for bias correction. Level set restrictions based on family non-labor income. Monotonicity restrictions based on individual age. See text for further details.



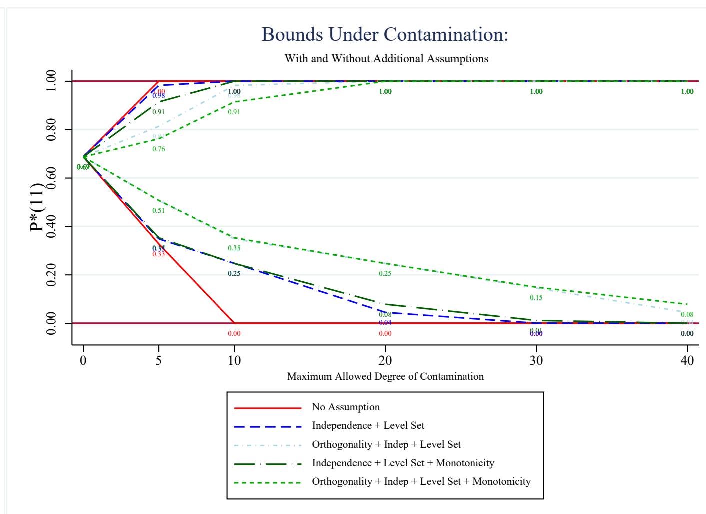
(A)



(B)



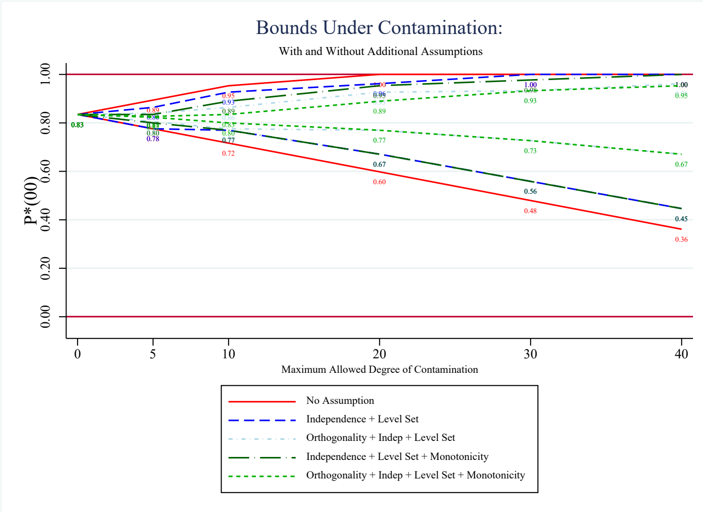
(C)



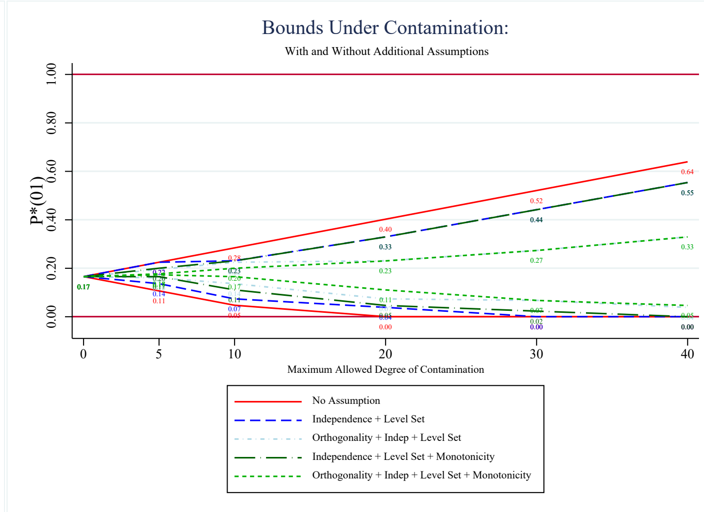
(D)

Figure A5. Conditional Probabilities of Labor Force Participation Under Various Assumptions and Maximum Misclassification Rates: 2004 Panel.

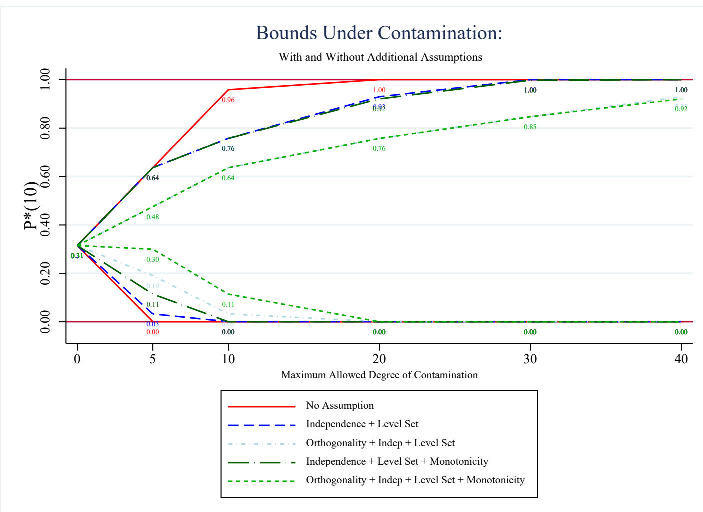
Notes: P*(00) = Pr(LF | Non-disabled), P*(01) = Pr(OLF | Non-disabled), P*(10) = Pr(LF | Disabled), P*(11) = Pr(OLF | Disabled). LF = labor force. OLF = out of labor force. Point estimates for bounds obtained using 50 subsamples of size N/2 for bias correction. Level set restrictions based on family non-labor income. Monotonicity restrictions based on individual age. See text for further details.



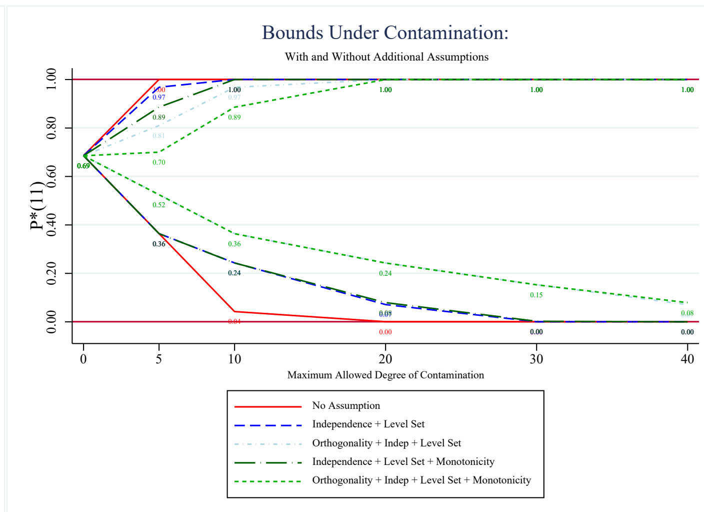
(A)



(B)



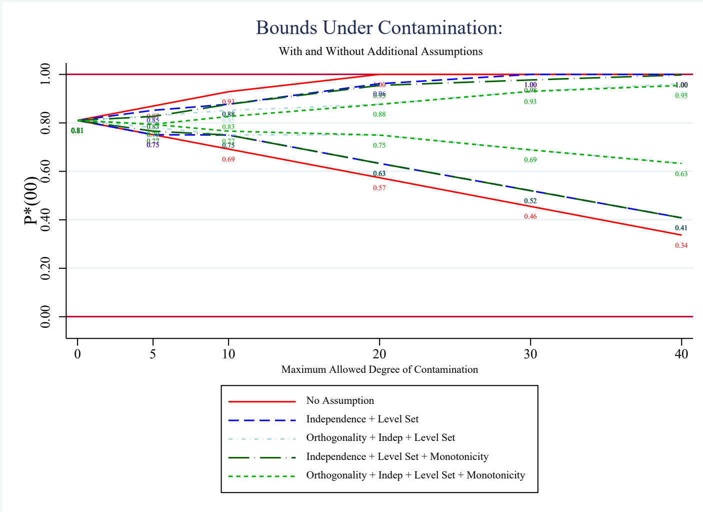
(C)



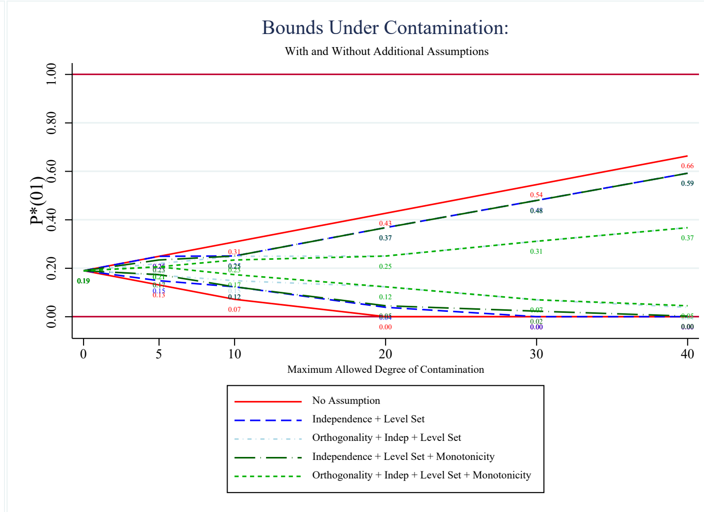
(D)

Figure A6. Conditional Probabilities of Labor Force Participation Under Various Assumptions and Maximum Misclassification Rates: 2008 Panel.

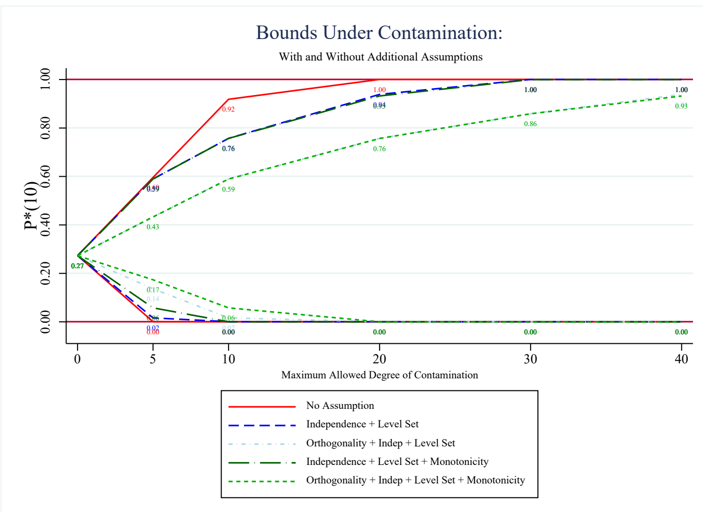
Notes: P*(00) = Pr(LF | Non-disabled), P*(01) = Pr(OLF | Non-disabled), P*(10) = Pr(LF | Disabled), P*(11) = Pr(OLF | Disabled). LF = labor force. OLF = out of labor force. Point estimates for bounds obtained using 50 subsamples of size N/2 for bias correction. Level set restrictions based on family non-labor income. Monotonicity restrictions based on individual age. See text for further details.



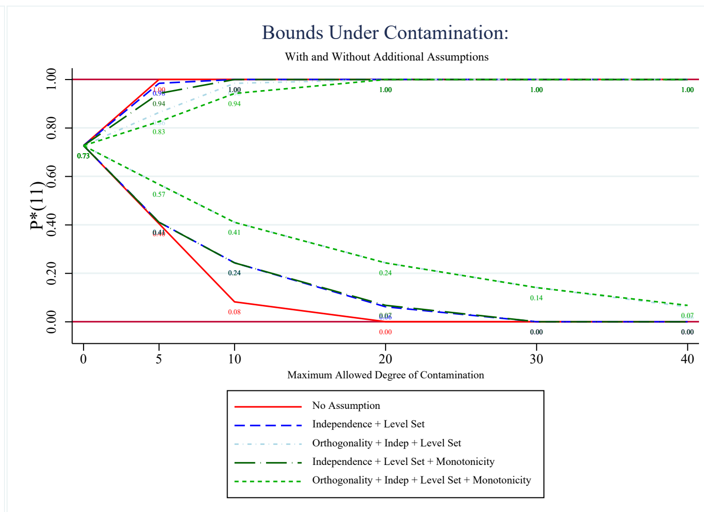
(A)



(B)



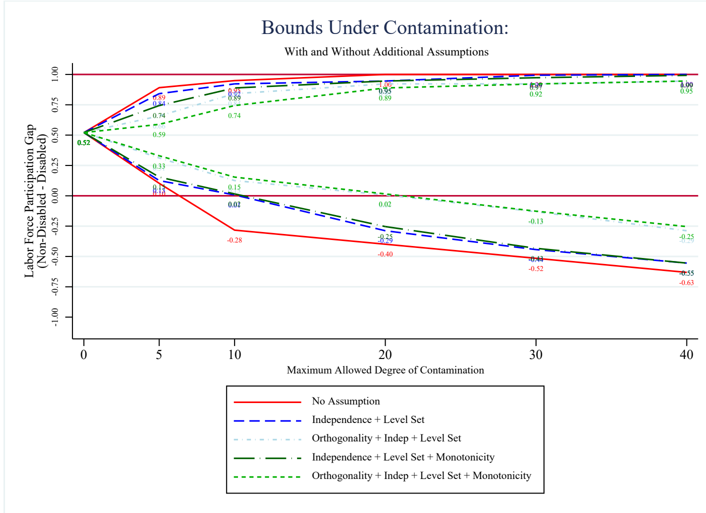
(C)



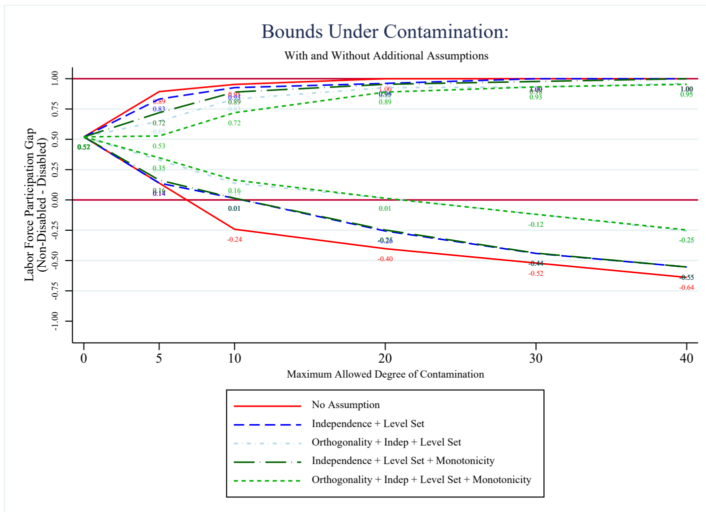
(D)

Figure A7. Conditional Probabilities of Labor Force Participation Under Various Assumptions and Maximum Misclassification Rates: 2014 Panel.

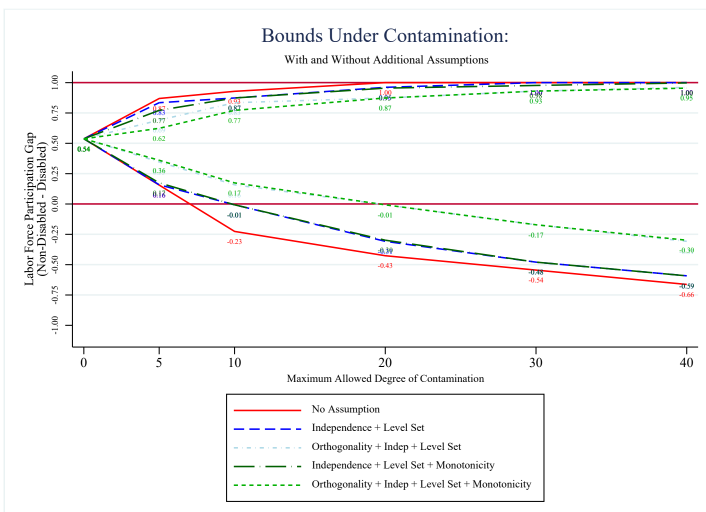
Notes: P*(00) = Pr(LF | Non-disabled), P*(01) = Pr(OLF | Non-disabled), P*(10) = Pr(LF | Disabled), P*(11) = Pr(OLF | Disabled). LF = labor force. OLF = out of labor force. Point estimates for bounds obtained using 50 subsamples of size N/2 for bias correction. Level set restrictions based on family non-labor income. Monotonicity restrictions based on individual age. See text for further details.



(A) 2004 Panel

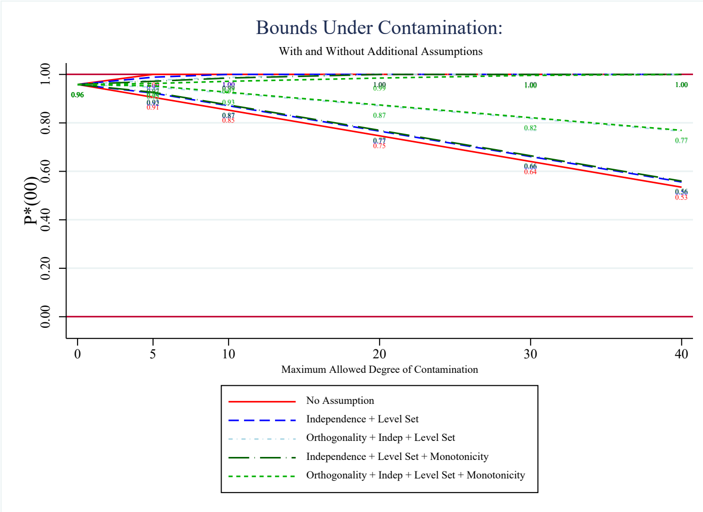


(B) 2008 Panel

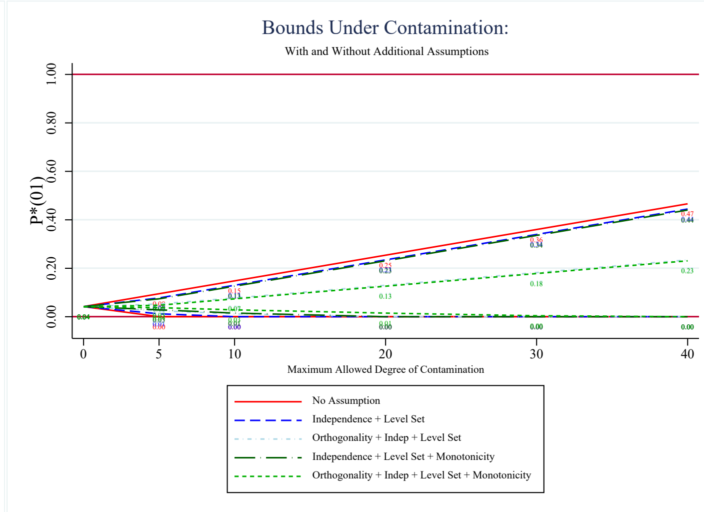


(C) 2014 Panel

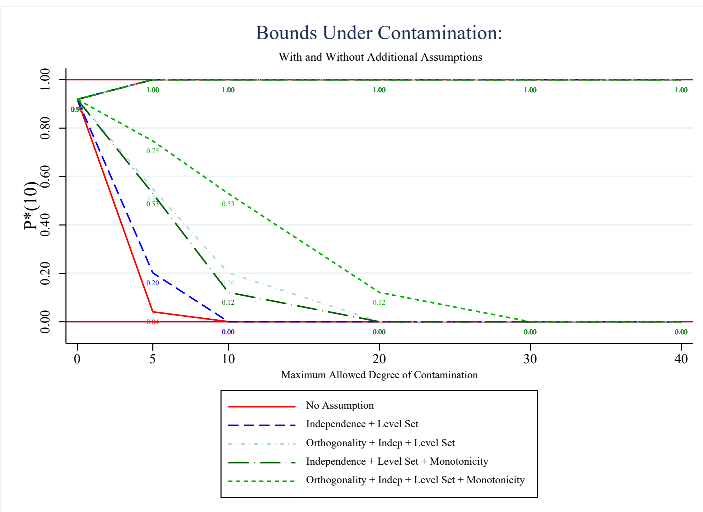
Figure A8. Labor Force Participation Gaps Under Various Assumptions and Maximum Misclassification Rates by Year. Notes: Employment gap is defined as the difference in the probability of being a labor force participant versus nonparticipant between the non-disabled and the disabled. Point estimates for bounds obtained using 50 subsamples of size N/2 for bias correction. Level set restrictions based on family non-labor income. Monotonicity restrictions based on individual age. See text for further details.



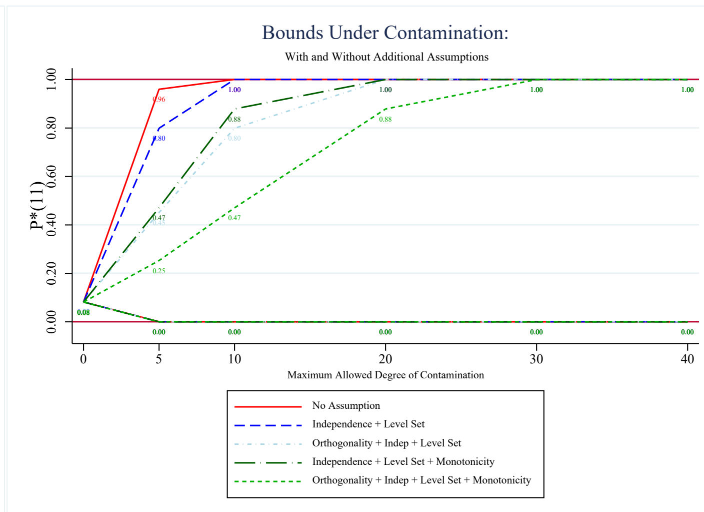
(A)



(B)



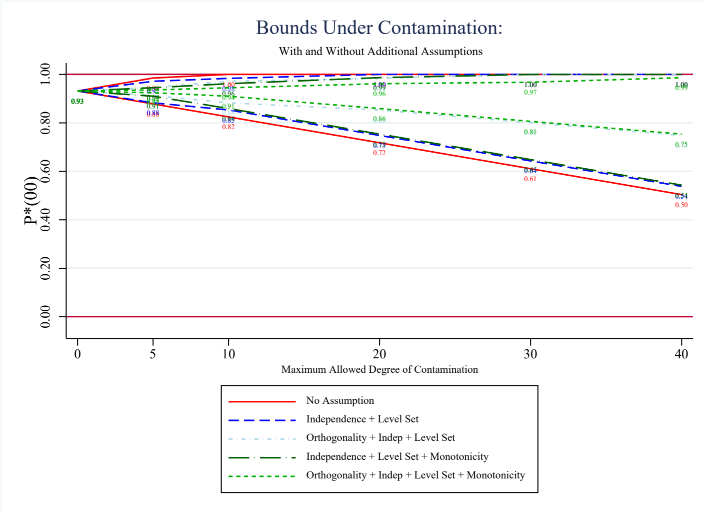
(C)



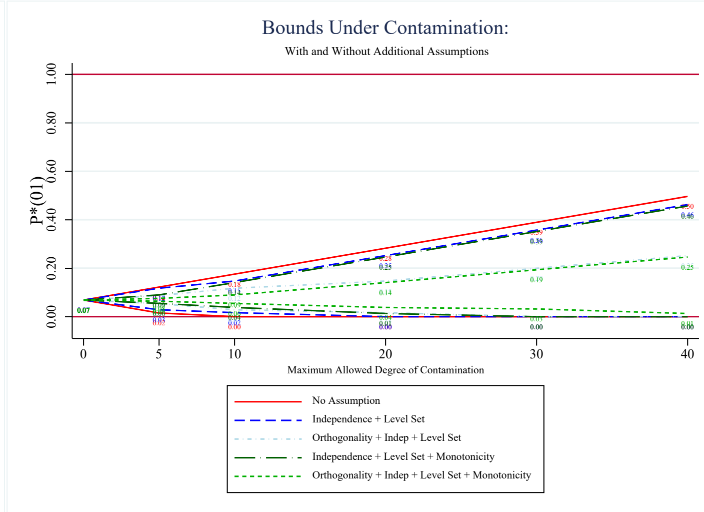
(D)

Figure A9. Conditional Probabilities of Employment & Unemployment Under Various Assumptions and Maximum Misclassification Rates: 2004 Panel.

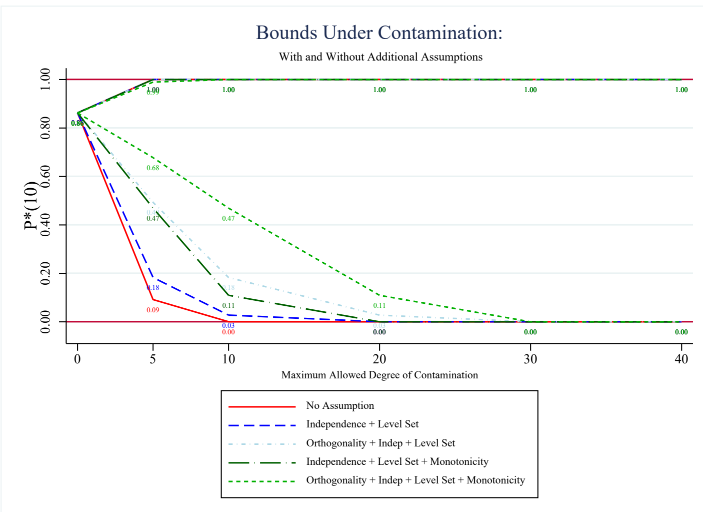
Notes: Sample restricted to individuals in the labor force. P*(00) = Pr(Emp | Non-disabled), P*(01) = Pr(Unemp | Non-disabled), P*(10) = Pr(Emp | Disabled), P*(11) = Pr(Unemp | Disabled). Point estimates for bounds obtained using 50 subsamples of size N/2 for bias correction. Level set restrictions based on family non-labor income. Monotonicity restrictions based on individual age. See text for further details.



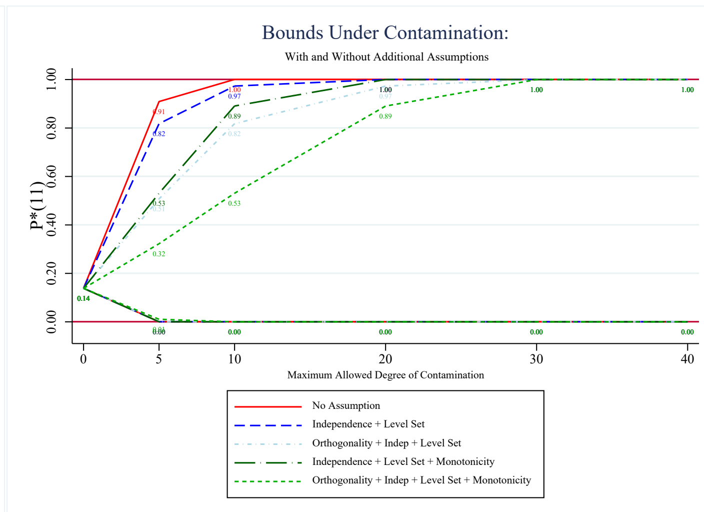
(A)



(B)

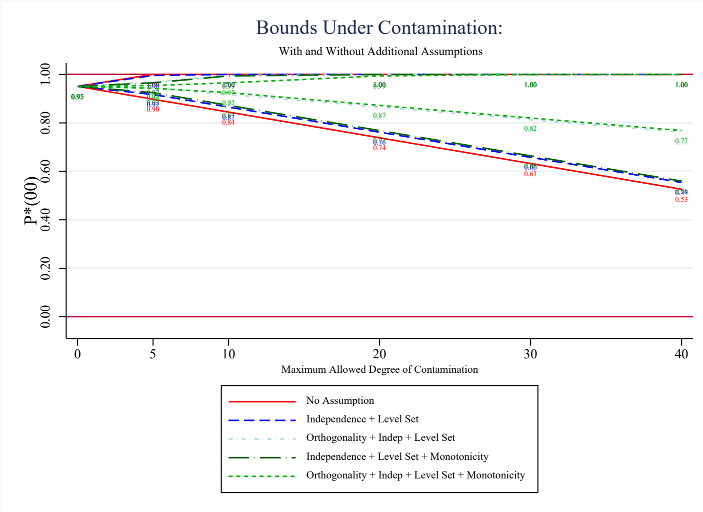


(C)

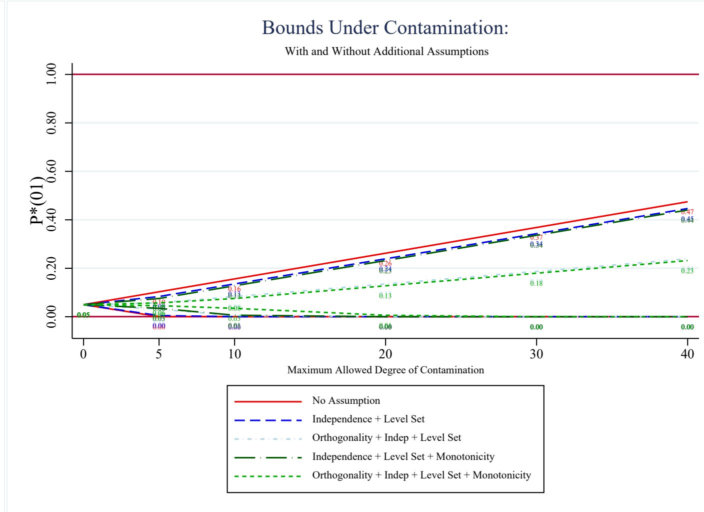


(D)

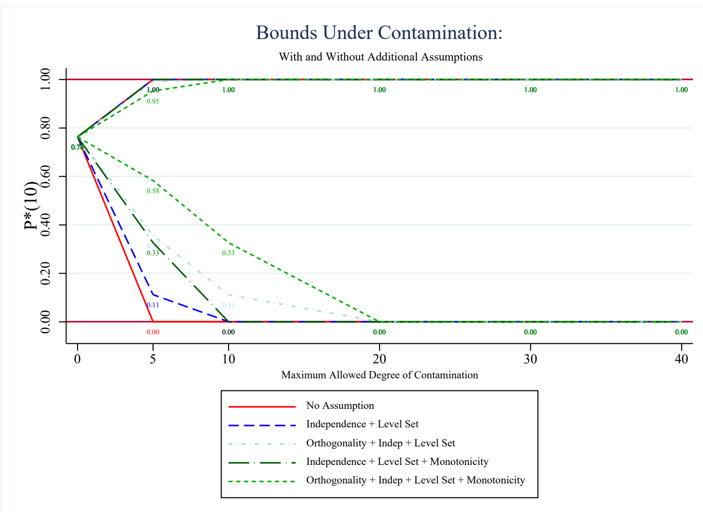
Figure A10. Conditional Probabilities of Employment & Unemployment Under Various Assumptions and Maximum Misclassification Rates: 2008 Panel.
Notes: Sample restricted to individuals in the labor force. P*(00) = Pr(Emp | Non-disabled), P*(01) = Pr(Unemp | Non-disabled), P*(10) = Pr(Emp | Disabled), P*(11) = Pr(Unemp | Disabled). Point estimates for bounds obtained using 50 subsamples of size N/2 for bias correction. Level set restrictions based on family non-labor income. Monotonicity restrictions based on individual age. See text for further details.



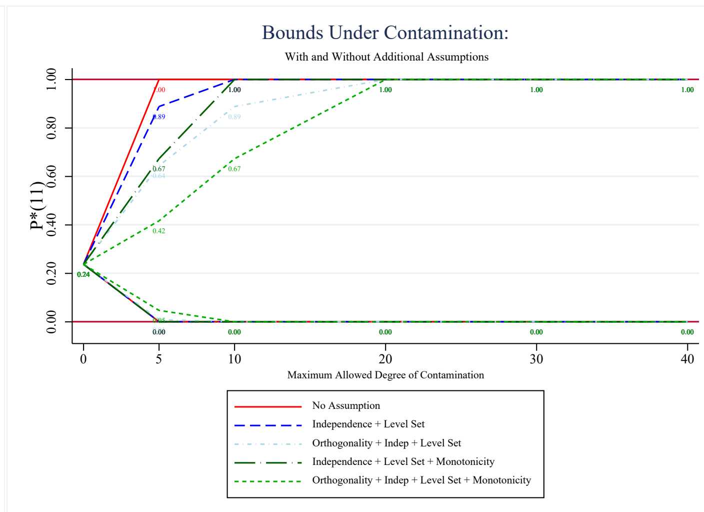
(A)



(B)



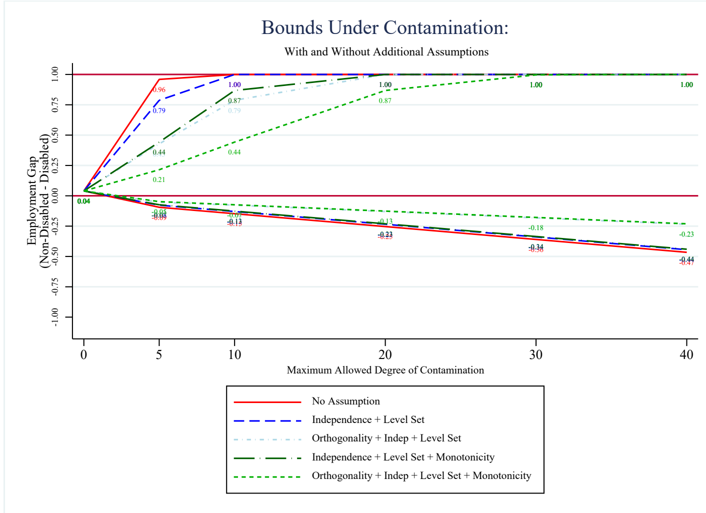
(C)



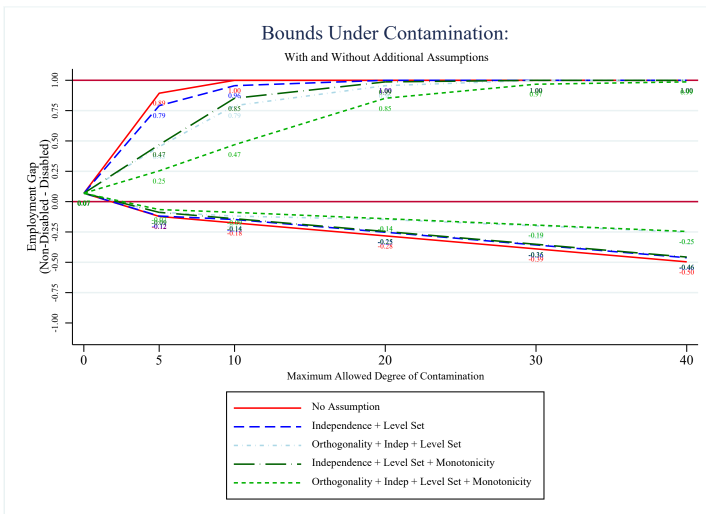
(D)

Figure A11. Conditional Probabilities of Employment & Unemployment Under Various Assumptions and Maximum Misclassification Rates: 2014 Panel.

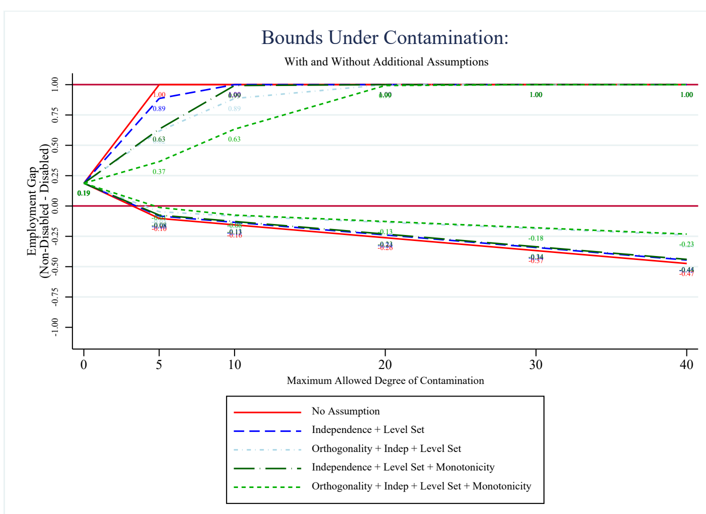
Notes: Sample restricted to individuals in the labor force. P*(00) = Pr(Emp | Non-disabled), P*(01) = Pr(Unemp | Non-disabled), P*(10) = Pr(Emp | Disabled), P*(11) = Pr(Unemp | Disabled). Point estimates for bounds obtained using 50 subsamples of size N/2 for bias correction. Level set restrictions based on family non-labor income. Monotonicity restrictions based on individual age. See text for further details.



(A) 2004 Panel



(B) 2008 Panel



(C) 2014 Panel

Figure A12. Employment Gaps Under Various Assumptions and Maximum Misclassification Rates by Year.
Notes: Employment gap is defined as the difference in the probability of being employed versus unemployed between the non-disabled and the disabled. Point estimates for bounds obtained using 50 subsamples of size N/2 for bias correction. Level set restrictions based on family non-labor income. Monotonicity restrictions based on individual age. See text for further details.