The Long-Run Impact of Temporary Disability Insurance on SSDI Claims, Earnings Stability, and Labor Force Participation

Extended Abstract

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Research Questions

Workers facing illness or injury often require time off work to recover or engage in treatment before returning to work. But access to temporary paid medical leave is limited. In 2017, only 72% of workers had access to employer-sponsored paid sick leave and 39% had access to short-term disability leave (Bureau of Labor Statistics, 2017). Moreover, access to paid leave is less common among low-income leave-takers, less than 50% of whom have access to leave with pay compared to 83% of higher income leave-takers. Only five states provide temporary paid medical leave for workers through state Temporary Disability Insurance (TDI) programs.[1]

Workers face both short- and long-run employment consequences of adverse health conditions and disability including increased likelihood of job loss, declines in work hours, and reductions in earnings and consumption (Meyer & Mok, 2016).[2] Lacking access to temporary paid medical leave for a work-limiting disability likely exacerbates reductions in earnings and job loss in the short-term but may also affect long-run employment outcomes because labor market instability in the short run leads to greater instability in the long run, and because the inability to access temporary paid medical leave may reduce the ability to recover from a health condition.

Lacking access to temporary paid medical leave may also affect long-run employment outcomes through the use of the federal disability program, Social Security Disability Insurance (SSDI), which restricts labor force participation, even during the application process, and discourages returning to the labor force (Autor, 2015; Autor & Duggan, 2006; Maestas, Mullen, & Strand, 2013). The SSDI program is growing rapidly; enrollment has increased from 3 million to 8.8 million recipients since 1990 (Social Security Administration, 2017) and the share of the working-age population receiving SSDI has more than doubled (Meuller, Rothstein, & von Wachter, 2016).

These twin problems of limited access to temporary paid medical leave and growing SSDI claims may be linked to each other and also to long-run employment outcomes including labor force participation and earnings (in)stability. Though there is a literature examining the relationship between SSDI claims and labor supply, there is only limited research examining the impacts of temporary paid medical leave on long-run employment outcomes and on future SSDI claims for individuals with a work-limiting disability. To bridge the gap in research on the impacts of temporary paid medical leave policies, this paper uses state-level TDI availability to answer the following research questions:

[1] TDI programs were also recently passed in Washington state and the District of Columbia. Many other states have legislation under consideration.

[2] Shaller & Stevens (2015), Strully (2009) and Sullivan & Von Wachter (2009) show that unemployment can also be a cause of poor health.

1. Does the availability of TDI increase or decrease long-run earnings, labor force participation, or employment instability for those with a work-limiting disability?
2. Does the availability of partial wage replacement through TDI programs reduce SSDI claims for these individuals?
3. Are there groups of workers by education, earnings, gender, or race for whom TDI availability is particularly useful in reducing SSDI claims and increasing the levels and stability of long-run earnings and labor force participation?

This paper makes several key contributions. We are the first to examine the impact of access to *temporary paid medical leave for an own-illness* on *long-run economic outcomes* including labor force participation and earnings, the instability of labor supply and earnings, and applying for and receiving SSDI. This contribution is enabled by the data we use which links data from the Survey of Income and Program Participation (SIPP) to Social Security earnings and benefits records which allows us to consider employment and benefit outcomes outside of the SIPP survey window for workers who report a work-limiting disability in the SIPP survey. Second, though there is considerable work examining how paid family leave affects the employment outcomes of new mothers, there is still very limited work on the benefits of temporary paid medical leave for recovering from a serious own-health condition even though these types of leaves represent 55% of all family and medical leaves taken (Klerman, Daley, & Pozniak, 2014).

The importance of these questions from a policy perspective is two fold. First, this work informs the current debate at state and federal levels on developing temporary paid medical leave policies by considering longer-term outcomes associated with such programs. If access to temporary paid medical leave improves economic outcomes in the long run and reduces SSDI claims, these benefits should be included in legislative debates about the costs of such programs. This contribution is particularly important because reductions in labor force participation of prime age workers and the growth of their SSDI usage are major policy concerns.

Second, this research can shed light on issues of inequality. Our analysis considers which groups of workers may be most helped by access to temporary paid medical leave. Improved access to such leave is likely to be most important for workers with fewer resources who have more limited access to paid leave and who are more likely to have lower labor force participation (Kreuger, 2017), to experience higher earnings instability (Carr & Wiemers, 2018), and to apply for SSDI (Autor & Duggan, 2006). If TDI programs result in more stable earnings and improved labor force participation, especially among less-educated and lower-earning workers, provision of temporary paid medical leave may have direct implications for reducing workplace inequality and promoting macroeconomic growth (Mian & Sufi, 2011).

Brief Literature Review

Definitions and Policies

Most workers have access to paid sick days through their employer, union-negotiated contracts, or state and municipal legislation. This workplace benefit is typically of short duration[3] and

[3] The Bureau of Labor Statistics (2017) reports that about 65% of all workers get 10 or fewer days of paid sick leave, regardless of length of time with their employer.

designed to accommodate routine, short-term illness like the flu. The Family and Medical Leave Act (FMLA) and state-level TDI programs are the two major policies directed toward safeguarding short-term leaves for the work-limiting disabilities that we examine in this proposal.[4] The FMLA allows for job-protected unpaid leave for up to 12 weeks for medically-certified serious health conditions (including pregnancy), to bond with a new child, or to care for an ill spouse, parent, or child.[5] About 60% of workers are covered by FMLA (Klerman et al., 2014).

TDI programs, which provide for partial wage replacement while on short-term leave for a temporary serious health condition, have been operating since the late 1940s in California, Hawaii, New Jersey, New York, and Rhode Island. Since the late 1970s, TDI programs also cover pregnancy-related leaves (in compliance with the Pregnancy Discrimination Act of 1978). New York and Hawaii TDI programs use private insurers while California, New Jersey and Rhode Island operate state-run programs, funded through employee and in some cases employer contributions. California, New Jersey and Rhode Island each recently extended their programs to cover short-term family leaves.

In California and New Jersey 55% of all medical and family leave claims in the 2014-16 period were for non-pregnancy own health reasons. These leaves averaged between 4 and 5 months in length. New Jersey reports on 15 major morbidity groups of non-pregnancy related disabilities. In 2016, the three most common reasons are musculoskeletal conditions (25%); accidents, poisoning and violence (17.5%); and neoplasms (10.7%) (New Jersey Department of Labor and Workforce Development, 2017; 2015; State of California Employment Development Department, 2018).

SSDI provides income replacement for non-elderly adults unable to work due to a physical or mental impairment that can be expected to last at least 12 months or result in death. About half of SSDI applications are eventually approved but the application process typically lasts between 1 to 3 years. Applying for SSDI requires individuals to be out of the labor market for extended periods, even if claims are eventually denied (Autor, 2015). Once receiving SSDI, few recipients leave (Autor & Duggan, 2006; Maestas et al., 2013).

The Relationships Between Health and Economic Outcomes

There is a vast literature on the relationship between poor health or disability and labor supply and earnings (see Currie & Madrian (1999) for a review of this literature). Much of the literature in economics focuses on the extent to which poor health causes reductions in wages, earnings, and work hours (Bound & Burkhauser, 1999; Charles, 2003; Meyer & Mok, 2016; Mok, Meyer, Charles, & Achen, 2008; Smith 2004). One theme of this literature is that poor health and disability affect work hours and labor force participation more than hourly wages but that the consequences for earnings can be large (Currie & Madrian, 1999). And, declines in earnings and hours can be persistent in the long run (Garcia-Gomez, van Kippersluis, O'Donnell, & van Doorslaer, 2013; Meyer & Mok 2016; Mok et al., 2008).

Economic shocks can also lead to poor health as job loss, job insecurity, and earnings instability can all generate adverse health effects (Adda, Banks, & von Gaudecker, 2009;

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[4] TDI does not provide wage preplacement for work-related injuries. Those are covered by Workers' Compensation programs, required in all states.
[5] Only workers who worked 1250 hours or more in the previous year for the same employer which has 50 or more workers within a 75-mile radius are eligible for FMLA.

Halliday, 2017; Schaller & Stevens, 2015; Strully, 2009; Sullivan & Von Wachter, 2009). A growing public health literature also suggests that precarious employment in temporary or flexible work arrangements has an adverse effect on health (Benach et al., 2014; M. Kim, C. Kim, Park, & Kawachi, 2008; Pirani, 2015).

Most directly related to our work is the work of Charles (2003), Mok et al. (2008), and Meyer & Mok (2016) who examine the long-run earnings trajectories of workers with a work-limiting disability in the PSID. Though Charles (2003) originally showed small effects of disability on earnings and work hours that generally rebounded within two years, subsequent analysis in Mok et al. (2008) and Meyer & Mok (2016) suggest very large effects (up to 79% reductions in earnings) of work-limiting disabilities in the long run, particularly for workers with chronic disabilities. The long-run effects of a work-limiting disability on earnings are smaller for those with a temporary disability who experience a loss of earnings of 14.5% in the year after reporting the disability which falls to 8% by the fourth year after onset of the disability.

Like Charles (2003), Mok et al. (2008), and Meyer & Mok (2016), we examine the long-run impact of experiencing a work-limiting disability. But, our work differs from these studies because we examine whether access to temporary paid leave through TDI reduces the long-run impact of a work-limiting disability. Unlike these studies, we do not differentiate between workers with chronic or temporary disabilities. This is partly a data restriction but also recognizes that chronic work-limiting disabilities may not be recognized as such ex ante. Finally, we consider the additional outcomes of variability in earnings and labor force participation as economic consequences of work-limiting disabilities.

SSDI and Employment

SSDI is a large and growing program. In 2015, SSDI paid $143 billion to nearly 9 million disabled beneficiaries and their spouses and children (CB0 2016) and the Social Security Administration projects that nearly one-quarter of 20-year olds today will claim disability by the age of 65 (Maleh & Bosley, 2017). There is a large literature examining the reasons behind the growth in SSDI claims (Autor, 2015; Autor & Duggan, 2003; 2006; Duggan & Imberman, 2009; Liebman, 2015) and the relationship between SSDI claims and labor supply (Bound, 1989; Maestas et al., 2013).[6]

But, there is only limited research examining the long-run impacts of temporary paid medical leave on future SSDI claims. Lindner & Nichols (2012) find that TDI claims are associated with a higher likelihood of applying for SSDI over a two-year time horizon but that there is little evidence of a causal link. At the state level, Coe, Haverstick, Munnell, & Webb (2011) find that TDI has a small negative effect on overall SSDI applications. Our work is most similar to Lindner & Nichols (2012) who also use data from the SIPP to link TDI availability to SSDI claims but do so only within the SIPP interview window.

Effects of Temporary Paid Leave on Employment

There are several reasons to think that temporary paid sick leave might improve employment outcomes and reduce SSDI claims. From the perspective of the employer, the availability of

[6] There is a large body of related research examining the relationship between unemployment rates, unemployment insurance and SSDI claims (Autor & Duggan, 2003; Black, Daniel, & Sanders, 2002; Lindner, 2016; Mueller et al., 2016; Rutledge 2011).

temporary paid sick leaves may provide an incentive to find accommodations that allow workers with an ongoing illness or disability to return to their job. And, it allows workers to seek treatments for injuries and illnesses that facilitates healing which might prevent or postpone re-occurrence of serious health issues while encouraging return to work. To the degree that workers taking a temporary extended health leave have continuous income while out of work and that job stability is associated with earnings stability, we would expect the existence of paid sick leave, to smooth earnings over time.

There is limited research that suggests that paid sick leave reduces job loss. Hill (2013), using Medical Expenditure Panel Survey data, finds that paid sick leave decreases the probability of job separation by 25%. Access to paid sick leave within the United States also decreases the likelihood of delaying or forgoing medical care (DeRigne, Stoddar-Dare, & Quinn, 2016), increases the likelihood of preventative medicine such as mammograms, pap tests, and endoscopies (DeRigne, Stoddar-Dare, Collins, & Quinn, 2017; Peipins, Soman, Berkowitz, & White, 2013), and reduces emergency department visits (Bhuyan et al., 2016). Returning to work while still ill – known as presenteeism – is more prevalent among workers without paid sick time (Johns, 2010) and workers under financial stress (Callen, Lindley, & Niederhauser, 2013). Though not directly related, the availability of paid maternity leave (covered by TDI in the TDI states), is associated with quicker return to work (Berger & Waldfogel 2004) and reduces the likelihood of leaving the labor force or changing jobs (Glass & Riley, 1998).

Data

The research questions link availability of partial earnings replacement through TDI for a work-limiting disability to two types of outcomes: longer-run earnings and employment stability, and application for and receipt of SSDI. Our empirical approach requires a dataset with five characteristics: long earnings histories including periods of zero earnings, SSDI application and receipt dates, geographic identifiers to identify TDI states, demographic and human capital characteristics, and health and disability information.

The best source of data including all of these elements is the Survey of Income and Program Participation Synthetic Beta (SIPP SSB) and the SIPP Gold Standard File (SIPP GSF). The SIPP is a nationally representative sample of the civilian noninstitutionalized population of the United States that began in 1984. There have been 14 SIPP panels since 1984, each panel lasts between two and four years, and each panel draws a new nationally representative sample of 14,000 to 52,000 households. The SIPP GSF links each individual with a valid social security number in a SIPP household in the 1984, and 1990 -- 2008 SIPP panels to their Internal Revenue Service (IRS) and Social Security Administration (SSA) earnings and benefits records through 2011 both prospectively and retrospectively. The full SIPP GSF is only available at a Census Restricted Data Center (RDC). However, the SIPP SSB is a public use synthetic version that provides outside researchers indirect access to the data because the Census Bureau agrees to run all analyses on the SIPP GSF.[7] We have been using the SIPP SSB in this way since 2015.

Earnings and SSDI Benefits

[7] The SIPP SSB is synthetic, meaning it is entirely imputed in such a way that means and relationships between variables are preserved in the data, so the Census Bureau can make the SIPP SSB available as a public use data file. Benedetto, Stinson, & Abowd (2013) describe the creation of the synthetic data in great detail.

Earnings histories in the SIPP GSF come from the Summary Earnings Records (SER) and Detailed Earnings Records (DER), which are co-maintained by the SSA and IRS. The SER includes FICA taxable earnings, so are capped at the FICA taxable maximum, and go back to 1951. The DER contains all earnings, including deferred and self-employment earnings, resulting in annual non-topcoded total earnings from 1978 to 2011. Also included are the number of FICA covered quarters that an individual worked in a year. Years in which individuals did not have any earnings are recorded as years with zero earnings.

SSDI benefits information comes from the 831 Disability File. Critical to our paper, the SIPP GSF contains application dates for both successful and unsuccessful SSDI applications. While the data only record a maximum of four applications, they always contain the first and last application dates. The data also include the amount awarded.

Individuals are matched to their earnings and SSDI benefits both prospectively and retrospectively. For example, a 50-year-old in the 1996 SIPP Panel would have FICA taxable earnings as far back as 1951, non-topcoded earnings from 1978 through 2011, and a record for any SSDI benefits applied for or received.

Geographic, Demographic, Human Capital, Health, and Disability Characteristics

In addition to the administrative earnings and benefits records, the SIPP GSF currently includes identifiers for educational attainment, race, gender, state of residence at the time of the SIPP survey, and whether an individual has a work-limiting or work-preventing disability. All of these come from the SIPP survey and cover only the SIPP survey window.

We follow Meyer & Mok (2016) and Charles (2003) and use a self-reported work-limiting disability to identify individuals with a disability. We do so because it is the only health measure currently in the SIPP GSF.[8] The measure of disability in the SIPP GSF covers the entire SIPP survey window – that is, an individual has a work-limiting disability if they experienced a work-limiting disability at least once during the SIPP survey window. Other characteristics from the time of the SIPP survey are also available including use of food stamps, AFDC/TANF, workers compensation, access to health insurance, wealth, employment status, and weeks worked which can be used as covariates in the models described below.

Sample Sizes and Match Rates to Administrative Earnings

Our empirical strategy allows us to pool all SIPP panels together. The sample size of the pooled data is, totaling 783,781 individuals. Table 1 shows how many individuals in the SIPP SSB report having a work-limiting disability, have applied for SSDI, and have both a work-limiting disability and have applied for SSDI, overall and in the five TDI states. Since the data are synthetic, these are not the actual sample sizes but our previous experience working with the SIPP GSF and SSB suggests that the totals in the actual data will be similar to the SIPP SSB.

Table 1. Sample Sizes (N) in the SIPP SSB

[8] Currie & Madrian (1999) have a comprehensive discussion of the issues associated with using self-reported disability or health status to examine the effect of health on labor supply which suggests that self-reported measures are good indicators of health but may be more subject to reporting bias. However, these measures are quite standard in this literature.

Work Limiting Disability		SSDI Application		Both Work Limiting Disability and SSDI Application	
Overall	TDI State	Overall	TDI State	Overall	TDI State
130,370	13,339	100,345	13,567	44,281	5,448

Missing data in the SIPP GSF are multiply imputed.[9] Missing administrative data arise when there is no valid social security number for linking. There is a flag in the data to differentiate between individuals who could be matched to their administrative earnings and benefits records and those who could not be matched. The match rate for most panels is quite high.[10] But, all estimations will be run on both a matched and full sample where missing observations are imputed using multiple imputation methods to test the sensitivity of our results.

Methods

Basic Empirical Strategy

Our primary research questions link the availability of TDI to employment and benefits outcomes over a long-time horizon of up to 27 years.[11] We observe each individual i in the SIPP GSF during one SIPP survey window which we refer to as time t. At time t we observe the disability status and state of residence (s) of individual i. We use the administrative earnings and benefit records in the SIPP GSF to follow the employment and benefit outcomes of individual i in each year $t + \tau$ where τ goes from 1 to 27.[12]

To estimate the effect of TDI access on long-run employment and benefit claims, we propose two methods. First, we compare the long-run employment and benefit outcomes of individuals with a work-limiting disability who live in states with TDI to those who live in states without TDI. Here we rely on the synthetic control methods in Abadie & Imbens (2006) to make comparisons of similar individuals living in different states. Second, we implement a difference-in-differences approach in which we compare the long-run employment and benefit outcomes of workers with and without a work-limiting disability who live in states with TDI programs to workers living in states without TDI programs. Because the availability of TDI should impact individuals with a work-limiting disability but have no effect on individuals without a work-limiting disability, those without a work-limiting disability provide a potentially useful control group for those who do. However, because individuals with a work-limiting disability may be quite different from those without a work-limiting disability and individuals in TDI states may differ from individuals in non-TDI states, we will combine this difference-in-differences approach with propensity score matching techniques to balance observable characteristics.

[9] Imputing missing data through multiple imputation may change in the next release of the SIPP GSF/SSB.

[10] In the 1980's and 1990's panels, the match rate hovers around 80%. In 2001, the match rate dropped to 47% because many SIPP participants refused to provide social security numbers. Beginning with the 2004 panel, the match rate increased to around 90% because the Census Bureau changed its matching procedures removing the necessity to explicitly ask for social security numbers. For our analysis, we will pool all panels together, the low match rate for one panel does not have a significant impact on the overall match rate of the pooled sample.

[11] The maximum number of years we can examine is 27 because the earliest year t is 1984 and the SIPP GSF includes administrative records through 2011.

[12] In practice, since the SIPP survey window is between 2.5 and 4 years in length and the last year observable in the SIPP GSF is 2001, $t + \tau$ ranges between 2.5 and 27 for the 1984 SIPP panel but only between 3 and 7 for the 2001 SIPP panel.

Sample

We have two main samples, one for each method in our empirical strategy. The first is a sample of individuals with a work-limiting disability who have not received SSDI at time t. The second is a sample of all individuals who have not received SSDI at time t.

Outcomes

We consider the effect of TDI access on four employment outcomes: earnings, labor force participation, and the instability of both of these measures over time. We measure earnings using the administrative earnings in the SIPP GSF which is the sum of all labor earnings in a calendar year including self-employment but excluding under-the-table earnings. Labor force participation is assessed based on two measures: having zero earnings in a calendar year, and the number of quarters of a calendar year in which an individual's earnings are above the Social Security earnings threshold for a covered quarter of work. We also assess the (in)stability of these measures over the period t to $t + \tau$ using within-person variances. Finally, we consider the effect of TDI on application for and receipt of SSDI.

Methods

We propose to estimate two sets of models. First, we estimate models in which employment and SSDI outcomes in $t + \tau$ are a function of whether an individual lived in a TDI state at t:

$$y_{is,t+\tau} = \beta_0 + \beta_1 TDI_{ist} + \beta_2 X_{it} + u_{is,t+\tau} \tag{1}$$

where $y_{ist+\tau}$ is one of the employment or SSDI outcomes described above for individual i in state s in time period $t + \tau$, or in the case of the instability outcomes, between t and $t + \tau$, X_{it} is a set of individual controls measured at t, and TDI_{ist}, is an indicator variable equal to 1 if the state s in which individual i resides at t is a TDI state. β_1 is the coefficient of interest. We estimate Equation (1) on the sample of individuals with a work-limiting disability at t. TDI receipt is not in the SIPP GSF data, and even if we added this variable to the SIPP GSF, it would not be observable outside of the SIPP survey window. Thus, this estimation approach gives the effect of TDI *access* on outcomes, not TDI receipt. We will return to this issue below.

Second, we consider a difference-in-differences model:

$$y_{is,t+\tau} = \delta_0 + \delta_1 TDI_{ist} + \delta_2 W_{it} + \delta_3 TDI_{ist}\, x\, W_{it} + \delta_4 X_{it} + \varepsilon_{is,t+\tau} \tag{2}$$

where W_{it} is an indicator for whether individual i had a work limiting disability at t, TDI_{ist} is an indicator for whether the state s in which individual i resides at t is a TDI state, and $TDI_{ist}\, x\, W_{it}$ is the interaction between the two. We estimate Equation (2) on the sample of all individuals. The coefficient δ_3 is the coefficient of interest, namely, the difference-in-differences estimate of the differential effect of TDI availability on outcome $y_{ist+\tau}$.[13]

[13] It is also possible to estimate the effects of TDI at all horizons simultaneously in an event-history approach by indexing the outcome at time t and using lags of the time since the SIPP interview. This specification would be similar to Charles (2003), Meyer & Mok (2016) who follow Jacobson, Lalonde, & Sullivan (1993).

The methods used to assess group differences in the effect of TDI on long-run employment and benefit outcomes simply amount to adding interaction terms to Equation (1) and (2) as follows:

$$y_{is,t+\tau} = \beta_0 + \beta_1 TDI_{ist} + \beta_2 TDI_{ist}\ x\ D_i + \beta_3 D_i + \beta_4 X_{it} + u_{is,t+\tau} \tag{3}$$

$$y_{is,t+\tau} = \delta_0 + \delta_1 TDI_{ist} + \delta_2 W_{it} + \delta_3 D_i + \delta_4 TDI_{ist}\ x\ W_{it} + \delta_5 TDI_{ist}\ x\ W_{it}\ x\ D_i + \delta_6 X_{it} + \varepsilon_{is,t+\tau} \tag{4}$$

where D_i is a variable describing the time invariant characteristics of individual i including race, educational attainment, and gender. We will investigate sample sizes to see if it is possible to look at the intersection of these groups such as less-educated women or African-American men.

Threats to Identification

In Equation (1), individuals with a work-limiting disability who live in a non-TDI state act as a control group for individuals with a work-limiting disability in a TDI state. In Equation (2) the difference in outcomes between individuals with and without a work-limiting disability in non-TDI states act as a control for the difference in outcomes between individuals with and without a work-limiting disability in TDI states.

The biggest concern is that the treatment and control groups differ from each other for reasons other than TDI access. TDI and non-TDI states may not be similar along dimensions that are important for long-run labor market outcomes and/or SSDI application. For example, consider the likely scenario where individuals without a work-limiting disability benefit more from strong labor markets than those with a work-limiting disability. If TDI states have stronger labor markets, or a higher density of individuals who generally have stronger labor market outcomes, than individuals with a work-limiting disability will appear to do worse in TDI states than non-TDI states (δ_3 <0) not because they actually have worse outcomes, but rather because individuals without a work-limiting disability have comparatively better outcomes.

Individuals may also consider a different range of health conditions to be work-limiting in TDI states compared to non-TDI states which would cause the underlying health of the groups to differ according to TDI access. If individuals consider more modest health conditions to be work-limiting in TDI states than in non-TDI states, β_1 and δ_3 would be too large in Equations (1) and (2), respectively. It is also possible that individuals move to work in TDI states when they know that they are in poor health and thus the group of people with a work-limiting disability may be in worse health, on average, in states with TDI.

Similarly, because health, broadly defined, can cause poor employment outcomes but may also be caused by poor employment outcomes, past employment histories may be different on average between individuals with and without a work-limiting disability, which means that future employment outcomes are likely to continue to be different. A similar issue exists for the probability of applying for SSDI benefits if the baseline probability of applying for SSDI benefits is higher among individuals with unstable employment regardless of health.

These concerns may manifest in a range of observed outcomes and covariates being quite dissimilar between groups, either between individuals living in TDI states and those living in non-TDI states or between individuals with a work-limiting disability and those without. As Imbens (2015) shows, even in the presence of exogenous treatments, such differences in the composition of treatment and control groups can alter the point estimates of OLS estimators, or, at the very least, make estimates of differences between groups less precise.

We propose to follow Imbens (2015) and Abadie & Imbens (2006) and use synthetic control methods – propensity score matching and/or weighting – to address these estimation problems. Propensity score matching and weighting both construct a counterfactual control group based on the predicted probability of being in the treatment group. First, we estimate a regression predicting the probability of having lived in a TDI state in the case of Equation (1) and also of having work-limiting disability in the case of Equation (2), based on time invariant and predetermined characteristics, including human capital and demographic characteristics from the SIPP survey, and historical earnings and labor force participation histories from the administrative earnings records in the SIPP GSF. We then use these predicted probabilities to balance the observable characteristics of the treatment and control groups by either matching individuals by their observed propensity scores, or by using the inverse of the propensity score to weight the full sample (Heckman, Ichimura, & Todd, 1997; Imbens, 2004). These methods can be combined with methods to trim samples and pretesting of exogenous outcomes to ensure a closer match between treatment and control groups (Imbens, 2015).

The long administrative earnings and labor force participation histories in the SIPP GSF prior to t, combined with demographic and human capital data from the SIPP survey at t allow us to construct uniquely suitable control groups. By matching individuals based on long-run trends in employment outcomes in addition to time-invariant human capital and demographic characteristics, the comparison is made between individuals with similar work histories and other characteristics relevant to labor market outcomes. Assuming that an individual's previous work history is an adequate summary of both individual and local labor market characteristics not accounted for by human capital and demographics, and the extent to which prior health affects work histories, then this approach supports a causal interpretation of the results. This approach is similar to Heckman et al. (1997) and Hotz, Imbens, & Klerman (2006) both of which match individuals with similar earnings histories to evaluate job training programs.

Future Work

We have been working with the SIPP SSB/GSF for five years to measures earnings inequality and earnings volatility. We have done some preliminary analysis on the SIPP SSB to identify our sample. The remaining work described will be completed before the PAA meetings in April.