Vocational Considerations and Trends in Social Security Disability

Amanda Michaud
Indiana University

Jaeger Nelson
Indiana University

David Wiczer*
Federal Reserve Bank of St. Louis

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Abstract

Along with health, Social Security Disability Insurance (SSDI) evaluates work-limiting disability by considering vocational factors including age, education, and past work experience. SSDI determinations based on these factors have grown three-fold since 1985. We use an unique state-level data-set to estimate how vocational demographics relate to SSDI awards and then assess the contribution of demographic change to SSDI trends. Although workers in their 50s are associated with higher SSDI award rates, secular increases in educational attainment should have offset the impact of population aging on rising SSDI claims, particularly those with Vocational Considerations.

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E-mail: ammichau@indiana.edu, jaegnels@indiana.edu, wiczerd@stls.frb.org. The authors thank Joel A. Feinleib at the SSA Advisory Board as well as the SSA for data on vocational acceptances. Thanks also to James D. Eubanks and the ALFRED team for valuable research assistance and help with digitization of SSA data and to ShinHyuck Kang. The views expressed herein are those of the authors and do not necessarily reflect the views of the Federal Reserve System, the Boards of Governors, or the regional Federal Reserve Banks.

1 Introduction

Social Security Disability Insurance (SSDI) protects workers against the inability to work due to health limitations. Program rules consider that different work options are available to different applicants, even those with similar health limitations. These "vocational" considerations acknowledge that advanced age, poor education, and limited work experience hinder one's ability to adapt to new work that might accommodate one's health limitations. Vocational considerations are of growing importance in overall SSDI determinations.[1] Figure 1 shows the share of awards and denials that have hinged on vocational considerations—where the outcome could have gone in the opposite direction if the applicant had been more or less skilled.[2] Figure 2 shows this trend is partly because more applicants reach the vocational consideration stage and partly because of a higher award rate conditional on reaching that stage. What is unclear is how much of the trend is provided by changes in how the rules are applied, the underlying demographics of the workforce, or changes in which demographics choose to apply. Disentangling the contributions of these forces is needed to gain insight into the solvency of the fund and to better understand labor market trends in general.

In this paper, we use a unique data set providing cross-state variation to estimate the relationships between demographics and SSDI claims and determinations. We then evaluate the contribution of changing demographics to trends in these SSDI measures over the past three decades, holding these relationships fixed. We focus on demographics explicitly conditioned upon at the vocational stage of the claim evaluation: age and education. This stage is increasingly prominent, as the share of determinations and awards with vocational considerations is rising. Furthermore, a focus on vocational factors is well-suited for this type of exercise. Age and education are objectively measured and acceptance criterion based on a vocational grid provides guidelines for leniency along these dimensions. As such our work is distinct from prior work focusing on health.

Our main finding is that mechanical changes in the composition of age, education, and

[1] Throughout the paper we consider decisions on first-time claims, not appeals.

[2] We refer to awards/denials/determinations as "vocational" awards/denials/determinations if they occur at the vocational stage (and hence have vocational considerations).

occupation demographics of the workforce have nearly zero impact on SSDI trends. While the aging population would predict an increase in SSDI, the changing education and occupational composition works in the opposite direction. We interpret this as suggestive evidence that in order for a demographic explanation to be valid there must have been a change in the association between demographics and SSDI application and award behavior. We look for clues as to why this relationship may have changed by identifying the states which have award rates much higher or lower than predicted by their demographics. Some of this variation may be due to regional economic conditions and cross-state variation in awards leniency. More research is required to ascertain the quantitative importance of such factors alongside health factors affecting medical awards (those without vocational considerations) which we do not study.

The extensive procedure through which SSDI applications are evaluated is discussed in detail in Section 2. It can be summarized as operating in three sequential stages: (1) eligibility, (2) medical, and (3) vocational. Claims are awarded at either the medical or vocational stage. Our findings for the importance of the three vocation-relevant demographics we consider: (i) age; (ii) education; and (iii) occupation, are as follows. The key age demographic associated with increased SSDI applications and vocational allowances at the national level is the 55-59 year-old age group. This group has the largest positive relationship with new applications and awards per capita (and also denials per capita as well). The same is true for vocational awards even though individuals aged 60-64 face more generous SSDI rules at the vocational stage. This suggests 55-59 is the pivotal age of entry contributing to the stock of individuals on SSDI. With regard to education, increased high school attainment diminishes the number of awards by lowering the application rate and increasing the denial rate at the vocational stage. This is aligned with the intent of the vocational rules. Finally, the effects of occupation differs in nuanced ways across age and education groups. In summary, our main result that demographics played no role in SSDI trends can be understood through the competing factors of age and education. While it is true that the baby-boom cohort has increased the share of workers over 50, the increased education of this cohort compared to previous ones offsets the contribution of their sheer size to SSDI trends. Occupational changes have almost no additional contribution.[3]

A second puzzle that emerges from our analysis concerns the increase in the award rate of applications reaching the vocational stage, particularly from 1985 to 2000. During this period there has been a secular increase in educational attainment of the workforce while education, according to the vocational grid, expands the types of work individuals can be expected to adapt to. Thus, higher education should lower the award rate at the vocational stage. Motivated by this contrast, we explore variation in SSDI application and award rates across states to better understand the vocational stage. In particular we decompose variation in awards per working-age capita into variation in overall applications, applications reaching the vocational stage, and the award rate at the vocational stage. The variation in total applications is the primary driver in the variation in vocational allowances across states followed by the variation in the conditional acceptance rate at the vocational state, accounting for 61% and 35% of the variation respectively. Digging deeper, we find states' total number of determinations is negatively correlated with their overall allowance rate, but positively correlated with their acceptance rate at the vocational stage. This suggests that high application states screen applicants out prior to reaching the vocational stage.

Interpreting causal relationships, however, requires further research. We cannot tell whether a high acceptance rate of applications reaching the vocational stage is a result of leniency— that states implement national rules with different standards. If implementation does differ, we cannot tell whether it also affects application rates. Nor can we tell whether states simply differ systematically in the joint distribution of health and vocational characteristics. The relationships identified in this paper motivate further research into these questions. We compare states' observed determinations with vocational considerations to those predicted by demographics as a first step in identifying common characteristics in high-award states to guide this research. Many such states are concentrated in the South and the Rust Belt, raising the hypothesis that regional economic factors related to industrial

[3]Although we do not study health directly, it should be noted that the conventional wisdom that occupations detrimental to one's health are in decline is not necessarily true. Michaud and Wiczer (2014) show health occupations have high risk of disability and Michaud and Wiczer (2016) shows that some these occupations have been growing rapidly.

change as well as the distribution of health contribute to variation in vocational award rates that could also be operative in change in these award rates over time.

The rest of the paper is organized as follows. In the next section we explain the SSDI determination process as it operates *de jure*. In Section 3 we discuss related literature. We then implement an empirical model to estimate the correlation between demographics and acceptances at the vocational stage in Section 4. In Section 5 and Section 6 we use the results from Section 4 to assess how much changes in vocational demographics contributed to the rise in SSDI rolls and where the cross-state variation in vocational awards comes from. Finally, Section 7 concludes.

2 SSDI Determination Procedure

SSDI determination is a multi-staged, sequential process (See Table 1 for key terms). The first stage determines an applicant's eligibility to claim disability benefits. In order to be eligible for SSDI benefits the applicant must not be currently engaged in Substantial Gainful Activity (SGA), defined in 2016 as having earnings greater than $1,130 per month for non-blind applicants. Furthermore, they must have accumulated a sufficient number of Social Security work credits prior to the onset of their disability. Social Security work credits are earned in accordance with an individual's wages or self-employment income. Up to four work credits may be earned per year with each credit requiring $1,260 in wages or self-employment income annually in 2016. The required number of work credits to be eligible for SSDI benefits increases with the applicant's age until they reach the age of 62, at which point they must have accumulated at least 40 credits over their lifetime with 20 of those credits having been earned in the 10 years prior to the onset of their disability.

Once an applicant has passed through the initial eligibility stage they move onto the second stage of the SSDI determination process which concerns the severity of the applicant's medical condition. If the applicant is healthy enough to perform basic work-related tasks, their application will be denied. Should an applicant's medical condition be labeled severe and be expected to last for at least one year or result in death, the condition is crossreferenced with the SSA's listing of impairments. If the applicant's condition meets or is equivalent to a condition on the listing of impairments their application will be accepted at this stage. However, if the applicant's condition is severe but does not meet or equal the medical conditions on the list of impairments they move onto the third stage of the SSDI determination process.

The third stage of the SSDI determination process considers the applicant's vocational ability to perform past or other work. At this stage applicants must also submit detailed information concerning the requirements of their recent past work. The Disability Determination Service (DDS) first assesses an applicant's *Residual Functional Capacity* (RFC)—the work they are capable of despite their medical limitations. Given an applicant's RCF and details concerning their past work, the DDS determines if an applicant is capable of performing past work. If the applicant is found to be capable of doing past work their application will be denied. If an applicant is found to be unable to complete past work, as it is usually done in the national economy, the DDS moves onto determining if the applicant can perform any other type of work.

In order to determine if an applicant is capable of performing any other type of work, the DDS first determines the applicant's maximum sustained capacity for work based on their RFC. An applicant's maximum sustained capacity for work is classified as sedentary, light, medium, or heavy/very heavy corresponding to the physical demands of the occupations within each category. Applicants capable of heavy/very heavy work are typically found not to be disabled earlier in the SSDI determination process. Using the *vocational grid*, their official guideline for determining the applicants maximum sustained work capacity, the DDS makes a final disabled/not disabled determination based on the applicant's age, education/literacy, and work experience.

The vocational grid defines age categories at 18-44, 45-49, "approaching advanced age" at 50-54, and "advanced age" at 55+. Older applicants are assumed to be limited in their vocational adaptability and, as a result, are more likely to be labeled disabled at the vocational stage relative to younger applicants. Education is broken down into three dimensions. The first is formal education, grouped as less than high school, high school, or more. The grid further divides individuals according to their literacy and ability to communicate in English. Finally, those with at least a high school education are divided between those whose education would provide direct entry into a skilled occupation and those whose education would not. An applicant's work experience is classified as unskilled, semi-skilled, or skilled. Skills are also labeled as either transferable or not transferable for those who performed semi-skilled or skilled work in the recent past. For applicants capable of medium work only, those with the lowest education and skill set in the approaching advanced age and advanced age groups are classified as disabled according to the vocational grid. Applicants with a lower capacity to work, light or sedentary only, face additional restrictions and, as a result, are more frequently accepted onto SSDI. We summarize the grid in Table 2.

3 Literature

Our paper belongs to an empirical literature assessing the rise in SSDI applications and allowances over time. Our paper is distinguished from the existing literature by considering the vocational aspects of the SSDI determination process as discussed in Section 2.[4] Specifically we use the explicit structure of the vocational grid to guide our decomposition of the rise in total and vocational SSDI allowances.[5] This has important implications for a number of structural investigations of Disability Insurance, such as Kitao (2014), Li (2015) and Low et al. (2015), who all richly model the way economic concerns affect the household side of the application decision. Michaud and Wiczer (2016), to our knowledge, is the only structural treatment that puts together both sides, household and SSDI, to consider how vocation not only affects individuals' earnings risk, but also affects the probability an individual's SSDI claim is accepted.

[4]Vocational considerations, and the vocational grid in particular, have also been discussed in relation to related questions, such as the work disincentives of SSDI receipt (Chen and Van der Klaauw (2008)).

[5]Lahiri et al. (1995) estimate relationships between individuals' characteristics and the outcomes of SSDI determination process at each stage using Micro data. We complement their work by estimating the relationship for a parsimonious set of demographics that can be measured nationally and explore the impact of demographic changes.

Rupp and Stapleton (1995) found that SSDI applications are countercyclical. They further documented that the business cycle's impact on allowances is less pronounced than it is for applications. Lindner and Burdick (2013) extended this work by exploring the demographics of the applicant pool over the business cycle. They found that the applicant pool contains more individuals with marginal to moderate health problems when the unemployment rate is high relative to periods of low unemployment. Furthermore, nearly the entire increase in SSDI applications and allowances surrounding high unemployment periods are either initially denied at the eligibility stage or accepted/rejected at the vocational stage. While a business cycle analysis is outside of the scope of this paper, our findings provide valuable insight into the relationship between demographics and SSDI outcomes at the vocational stage.

The methodological approach used in this paper is most similar to Liebman (2015). Liebman analyzes the impact of an ageing population, SSDI eligibility, and changes in the health of the beneficiary population on total SSDI allowances from 1985 to 2007. He finds that SSDI allowances increased as the baby-boomer generation entered peak SSDI ages (50-64). In this paper we extend that work and look within the SSDI program, at how demographics affect total and vocational SSDI allowances and denials. This means we also introduce other vocationally-relevant factors, education and occupation, which work in the opposite direction of aging. In the late 1980s legislative changes increased SSDI allowances through the early 1990s. Furthermore, the rise in the female labor-force-participation rate increased the SSDI eligibility among women during the 1990s raising SSDI allowances. Lastly the fall in mortality rates among SSDI beneficiaries slightly increased the number of individuals receiving SSDI benefits. Our paper extends the analysis to better match the SSDI determination process by including educational attainment and occupational factors.

Coe et al. (2011) explores the determinants of intra-state and inter-state variation in SSDI application rates. They find that an increase in the share of a population with less than a high school education, or a post-graduate education, lowers the SSDI application rate while the share of a state's population with "some college" is positively correlated with the application rate. We extend this result by analyzing the relationship between educational attainment and SSDI allowances and denials at the vocational stage. Our findings suggest that increased educational attainment amongst those aged 55-64 has resulted in fewer allowances and more denials at the vocational stage.

4 Vocation-Related Demographics and Award Rates

In this section we estimate how vocation-related demographics affect SSDI applications, allowances, and denials. We construct a unique state-level panel from 2001-2015 that contains information on states' demographic and SSDI program characteristics (see Appendix B for details). Using pooled OLS, we estimate the effect of a set of state demographics on their respective SSDI vocational acceptances, vocational denials, total applications, and total denials. Data availability restricts our sample for the vocational stage estimations to 2001-2003, 2010, and 2012-2015 for allowances and 2003-2004, 2010, 2012-2013, and 2015 for denials.

Allowances and denials are in terms of incidents per 100,000 individuals in the state's working-age-population (18-64). Our set of state-level demographic controls consist of the cross-product of age, education, and occupation. Guided by the vocational grid break points, we partition the population in three age groups, those aged 18-54, 55-59 and 60-65. We further partition the later two groups for which vocational consideration are most relevant by education and occupation. We distinguish between those individuals with less than a high school education, those who completed high school but have no college, and those with at least some college. The final demographic characteristic concerns the within age-education mix of occupations. We include regressors for those with more than a high school education, split by age group, and leave individuals aged 18-54 as the reference group.

We group occupations into three categories in the spirit of Autor et al. (2003). We use the Bureau of Labor Statistics Standard Occupational Classification (SOC) scheme to define occupations (SOC 1-16). The first group includes those occupations that entail cognitively intensive tasks. These included occupations in managerial, professional, sales, clerical, and administrative professions (SOC 1-4). The second group includes service related occupations that entail manual but non-routine work (SOC 5-9). The final group includes occupations that entail routine manual labor, such as those working in agriculture, construction, production, and manufacturing (SOC 10-16). This grouping of occupations is appropriate as the type of tasks necessary to work in an occupation are taken into consideration when determining a SSDI applicant's "maximum sustained work capability", and ultimately their allowance or denial status at the vocational stage.

Our main regression results are in Table 3 of Appendix A. It takes the form:

$$Y_s = \sum_{i,j,k} \beta_{i,j,k} \text{ Education}_i \times \text{Occupation}_j \times \text{Age}_k + residual_s$$

where Y_s is the state-level data on vocational acceptances, vocational denials, total applications, and total denials per 100,000 individuals in the working-age population. The regressors are the fraction of the working-age population in each demographic bin. Its coefficients, $\beta_{i,j,k}$, are used to compute the contribution of demographic and occupation groups on vocational acceptances, vocational denials, total applications, and total denials. To summarize the results, Table 4 shows the marginal effects of increasing the share of a demographic group by one percentage point as well as the total effect of each group within the population.[6] Table 5 further breaks this out by occupation.

We find that it is not the individuals with the least vocational capacity—the oldest and least educated—who are driving vocational acceptances. Instead, the slightly younger individuals, aged 55-59, that have the largest effect on vocational acceptances. Using our estimated coefficients we can compute the marginal impact of increasing the share of the working-age population in a particular demographic group by one percentage point on vocational acceptances, vocational denials, total applications, and total denials per 100k individuals in the working-age population. Increasing a state's population aged 55-59 year-old without a high school degree by one percentage point would add 38.69 vocational acceptances per 100k individuals in the working-age population; increasing the population share of the same age group, but with a high school degree, by one percentage point would add

[6]All share shifts are moving population into the group considered relative to the reference group aged 18-54.

4.84. In contrast, the effect of the same increase in the share of the population aged 60-64 with and without a high school degree is an additional -1.80 and 4.66 vocational acceptances per 100k individuals in the working-age population.

Critically when evaluating the total contribution of each demographic group, the relative size of the groups partially mitigates the effects on a per-person basis. For example the marginal effects on vocational denials per 100k individuals in the working-age population of shifting the share of the working-age population towards those aged 55-59 with and without a high school diploma by one percentage point are 22.35 and 91.34 respectively. However, as the size of the age-group with a high school diploma is larger than those without a high school degree (3.1% compared to 0.6% of the working-age population) the total effect on vocational denials per 100k individuals in the working-age population is larger for the group with a high school diploma despite having a lower marginal effect (70.79 relative to 53.48).

The slightly younger individuals aged 55-59 also drive total applications while the oldest individuals aged 60-64 play a smaller role. Marginal effects for total applications and total denials are shown in Columns (3) and (4). We calculate that increasing the share of individuals aged 55-59 without a high school degree by one percentage point would add 196.51 total applications per 100k individuals in the working-age population; increasing the share by the same amount for those with a high school degree would add 49.16. The effects for the older age group (60-64) with and without a high school degree is an additional 6.99 and -12.11 total applications per 100k individuals in the working-age population respectively.

Why is it that the oldest group has a smaller total affect on applications and vocational awards than the slightly younger group? The most obvious answer is that the new-award rate peaks for individuals in their mid-50s. This result must be interpreted within the context of the time period we study, 2003 and 2010 onward, which is heavily influenced by the Great Recession.[7] In this period the employment situation may have been especially bad for the 55-59 year-old demographic without tertiary education, resulting in more applications from those on the margin of applying for SSDI. The increase in applications from the 55-59 year-old demographic without a tertiary education resulted in an increase in both total

[7]This choice was not ideal, but a consequence of limited data access.

and vocational denials. Moreover, the high application rate also spilled over into vocational acceptances which also increased among this age-group, and especially among those without a high school education. This is again consistent with the structure of the vocational grid and the findings of Lindner and Burdick (2013) in which the applicant pool surrounding recessions contain more individuals with more mild to moderate heath problems relative to normal economic times. These are the individuals whose final SSDI determinations are based on vocational factors.

The differences across occupations bolsters the story that economic circumstance play a roll driving both application behavior and vocational allowances. Occupations 10-16, which are tightly tied to the manufacturing industry, have both higher acceptance and denial rates at the vocational stage for the 55-59 year-olds with less than a high school education. This can be due to the occupation's economic circumstances, which are driving higher application rates for those with and without qualifying conditions. Duggan and Autor (2006) provide a rationale for this behavior. They find high application rates in areas that have experienced "trade-shocks," defined as high job displacement from foreign manufacturing competition. Our evidence shows that vocational considerations are key for this corresponding demographic group.

5 Vocation-Related Demographics and Trends in Awards

In this section, we consider the contribution of changing demographics to the trend in national award rates. We hold fixed the marginal contribution of each group using the coefficients from our regression in Table 3 and then vary the composition of each demographic factor. This exercise presents suggestive evidence that while the changing age structure has contributed to the rise of total determinations and vocational awards, changes in within-age education and occupation composition works to decrease both the number of total determinations and vocational awards. The majority of the rise of vocational awards cannot be attributed to compositional change of the demographic groups, thus indicative of a change in the groups' marginal contributions.

The demographics considered are broad categories: age, education, and occupations. So, to extract the marginal effect of a broad demographic group from the specification of Table 3, we integrate over component groups. For example, the contribution of the group of high school graduates aged 60-64 in production related occupations is given by their population size multiplied by the single coefficient on that variable. The contribution of the group of aged 60-64 is given by the sum of the combination of the education and occupation subgroups in that broader demographic.

We begin by predicting the total determination and vocational award rates using the true demographics in 1985 and adjusting the estimate by a constant to hit the exact level. From here, we calculate the counterfactuals shown in Figures 3 and 4. Details of our methods are in Appendix C. First, we predict the time series from 1986-2014 as though only the age structure of the economy had changed. More precisely, we feed-in changes in the size of the population aged, 18-54, 55-60, and 60-64, but we keep the education and occupation composition within each group fixed at its 1985 level. This is the line labeled "Contribution of Age." The next prediction incorporates the observed changes in education within these groups in addition to the change in size across age groups. This is the line labeled "+ Education." Finally, we show the full prediction incorporating actual changes in all demographics we consider. This is the final line labeled "+ Occupations" in which we add the actual changes in occupational shares by subgroup, (aggregate shares shown in 5). Figure 3 applies this methodology to vocational acceptances and Figure 4 applies this methodology to total determinations.

Overall, we find no demographic change accounts for more than 16.5% of the rise in the vocational acceptance rate. In fact, the contribution of changing age shares alone does not increase the vocational acceptance rate until the year 1995. This may help explain the slow-down in the rise of the vocational acceptance rate during the 1990s. The same story holds for the impact of ageing on total determinations, accounting for 18.5% of the increase. When we turn our attention towards the contribution of education we find that the increased education of the population lowers the total determination rate. In fact, it more than cancels out the effect of the ageing of the population. Increased high-school attainment has also diminished the per-capita incidence of awards with vocational considerations. This is consistent with Table 4, which shows the high school educated have a lower acceptance ratio at the vocational stage than those without a high school degree. This is evidence that SSA vocational-grid rules are operating as they were intended; they are more stringent for the more educated at the vocational stage.

The changing occupational structure of the population is working against the rise in both the vocational acceptance rate and total determination rate. Figure 5 shows the share of the working-age-population within each of our three occupational groups: (1) SOC 1-4, (2) SOC 5-9, and (3) SOC 10-16. Highly skilled professional, managerial, and service related occupations have been increasing while manufacturing and production related occupations have fallen. As discussed in section 4, the manufacturing and production related occupations are the most influential for SSDI rates. Fewer workers in these decaying occupations should result in fewer workers applying for SSDI and being accepted at the vocational stage.

We explained in our discussion of the regression results that the contribution of any age cross education group depends on the occupational composition within that age group; the marginal effect of an additional individual; and the size of the group within the population. Figures 3 and 4 show the total estimated contribution of each disaggregated demographic group to the trends in new vocational awards and total determinations, respectively. They show that the most important group, those individuals aged 55-59 without a high-school degree, are predicted to contribute less to both total determinations and vocational award rates over time. This is primarily because the group is shrinking. The share of the population in the group fell from 1.7% in 1986 to 0.6% in 2015. The occupational composition within the group changed only slightly from 55% in manufacturing occupations in 1986 to 50% in 2015. Also of note is the fact that individuals in the same age group (55-59) but with a high school degree are predicted to increase their contribution to the total determinations, but not to vocational awards. Instead, we see this group contributing to the rise in total and vocational denials. This comes through the expansion of the size of the group, which increased from 2.5% to 3.3% of the population from 1986 to 2015, and because the share of workers within the group working in manufacturing occupations expanded from 14% to 30% over the same time period. The fact that they contributed more to the total determinations than vocational awards is consistent with the design of the vocational grid. Although this group has been growing over time, individuals with more education should be less likely to receive vocational awards.

If changes to the educational and occupational composition predict that application rates and vocational awards should have fallen, why then have they expanded instead? The remaining variable is whether the behavior of individuals within our demographic cells—their probability of applying—has changed over time. With state-level data alone, which is all that is available for the longer sample, we can not extract the change in applicant quality by demographic. This prevents us from distinguishing between a general increase in applications of lower quality or a particular group driving the trend. Some is likely due to the particular time period over which our regressions are estimated. From 2010-2015, they are heavily influenced by recessionary years. We found individuals in occupations that are in long-term decline, the production occupations (SOC 10-16), were most likely to apply and to receive a vocational award (Table 5). Our decomposition assumes this to have always been the case historically. Then when we perform the counterfactual accounting exercise, we naturally predict falling application and award rates as these occupations shrink. Probably, the application and award rates for these groups grew during the recessionary period relative to historic rates and this biases our exercise.

Finally, we conclude this section with a note on SSDI denial rates. Figure 1 depicts total SSDI applications, denials, and denials made at the vocational stage. The difference between denials and denials at the vocational stage captures those denials based on eligibility and/or a failure to meet the SGA requirement. Notably, we see a substantial increase in denials of all types beginning around 2000. This may reflect an increase in applications that do not meet the basic eligibility requirements or an increase in the general health of applicants, a possible result from the two recessions contained within these years.

6 Cross-State Variation in Vocational Awards

We have provided evidence that the four-fold increase in vocational acceptances per insured individual at the national level can not be accounted for by mechanical changes in the composition of demographic characteristics related to the vocational grid. Two explanations remain to account for the residual. First, there are vocational grid-related demographic factors that we did not consider. These include literacy and English-proficiency. The second explanation is a change in the incidence rate while holding demographic factors constant. The incidence rate of vocational acceptances per working-age-population is the cumulation of each stage in a three-step process. [8] The first step is the total determinations per working-age person in a given year. Total determinations reflect the application propensity of the population. The second step is the share of determinations made at the vocational stage. This reflects either a change in the de facto implementation of the SSA rules or a change in the *health* composition of the workers that apply. If applicants become marginally more healthy—that is, they maintain a work-limiting disability but do not satisfy "meets" or "equals" requirement for key medical decisions—then, a larger share will pass to the stage where vocational factors are considered. The third step is the acceptance rate conditional on passing to the vocational stage. This reflects again either a change in de facto implementation of the SSA rules or a change in the composition of the workers that apply. However, this time the relevant compositional change relates to *vocational* factors, not the health composition of the applicants as in the previous stage.

Table 6 in Appendix A shows that variation in total determinations (roughly total applications) per 100,000 people in the working-age-population differs substantially across states. The national mean is 988 and the standard deviation across state is 293. States above the national average are primarily states along the Rust Belt, Lower Midwest, and in the Southeast. Differences in total acceptances are mitigated by differences in the acceptance rate. The standard deviation in total acceptances is 85. If states only differed in determinations per working-age-capita, and had the same total acceptance rate equal to the national av-

[8] For our aggregate analysis we use disability awards per insured, but we do not have access to this data at the state-level at the time of writing.

erage, the standard deviation would be 100.5. This is because states' acceptance rates are negatively correlated with determinations per working-age-population (coefficient of correlation is -0.46). The vocational acceptances go in the opposite direction, but not by much: the actual standard deviation is 60 and the standard deviation with a fixed vocational acceptance rate is 54. Together these facts suggest that states with disproportionably high application rates screen out applicants before the vocational stage. That is, a share of the additional applicants do not meet requirements based on either substantial gainful activity or work-limiting disability. The final two columns show variation in how many applicants reach the vocational stage and how many within the group that reach the vocational stage are accepted.

In Table 7 of Appendix A, we isolate the various sources of vocational acceptances in individual states. The exercise we perform is as follows. The actual vocational acceptances for state s can be expressed as the following product:

$$\begin{aligned}\text{Vocational accept}_s = &\ \text{Total Determ.}_s \times \text{\% Determ. with Voc Consideration}_s \\ &\times \text{\% of Determ with Voc Considerations Allowed}_s\end{aligned}$$

To construct counterfactual vocational acceptances, we set two of three of the variables on the right-hand side to the national average thus allowing only one to differ across states. For example, in "Accept Rate at Voc. Stage" column, we allow only the conditional acceptance rate at the vocational stage to differ across states:

$$\begin{aligned}\text{Vocati}\widehat{\text{onal accept}}_s = &\ \overline{\text{Total Determ.}} \times \overline{\text{\% Determ. with Voc Consideration}} \\ &\times \text{\% of Determ with Voc Considerations Allowed}_s\end{aligned}$$

This suggests which stage contributes most to individual state outcomes. For example, Alabama's high vocational acceptance rate is driven by high total determinations whereas Louisiana's is equally attributable to both a high level of total determinations and a high conditional acceptance rate at the vocational stage. In states with acceptance rates below

100: Arizona, Hawaii, and Utah; all three factors must be working together.

To aggregate the information in Tables 6 and 7, we statistically decompose the overall variance in total vocational acceptances. Let Y be total vocational acceptances and X_j for $j = 1, 2, 3$ correspond to each of the components on the right hand side of Equation 6.1. First take a log transformation: $ln(Y) = \sum_{j=1}^{3} ln(X_j)$ and re-label $ln(Y) = \hat{Y}$ and $ln(X_j) = \hat{X}_j$. Then write the variance as:

$$Var(\hat{Y}) = \sum_{j=1}^{3} Var(X_j) + 2[Cov(X_1, X_2) + Cov(X_1, X_3) + Cov(X_2, X_3)]$$

Table 8 shows the percent contribution to the variance of log total acceptances of each factor in Equation 6.1. The variance of log total acceptances is 0.136. Variance in total determinations is the largest factor increasing the variance of total vocational acceptances. It alone would predict 61% of the total variation. The conditional acceptance rate at the vocational stage would contribute another 35% of the variance. The key mitigating factor is that the conditional acceptance rate is negatively correlated with the other two factors. This reduces the final total variance by 9%.

The correlation matrix in Table 9 shows that states that have more applicants reaching the vocational stage are more likely to reject applicants at that stage. What we cannot tell from this decomposition is whether this negative correlation is a result of individuals with different health and vocational factors applying in high vocational acceptance states or if it is a difference in how the rules are applied.

The main lesson of our cross-state analysis is that variation in the application rate mainly drives variation in the vocational award rate. While it is true that states with higher application rates reject more applicants at both the medical and vocational stages, they still allow more vocational awards per capita. Therefore, to understand cross-sectional variation one must not only consider how the decision to apply varies across states for reasons other than the demographics we study, but also why the acceptance rate at the vocational stage does not adjust to offset this. Understanding which factors drive differences in the cross-section provides a good starting point to evaluate whether the same factors have influenced time-series trends. For example, states with the highest application rates are concentrated in the South and Rust Belt states. One hypothesis is that there are additional vocational factors related to regional economic conditions that we did not consider in this study.

7 Conclusion

In this paper we investigated the role of demographics in SSDI trends, focusing on demographics related to vocational considerations. We find the 55-59 year-old demographic is an important driver of awards, but also of denials, through their high application rates. Attainment of a high school degree lowers awards both through lower application rates and a higher rate of denial at the vocational stage. This is inline with the *de jure* objective of the vocational grid in the SSDI award process. The vocational grid also treats occupations in an interesting way. Workers in their 50s in service or production sectors drove the incidence of awards with vocational considerations, but they also contribute greatly to overall applications and awards at the medical stage.

The intuitive relationship between vocational related demographics and award outcomes makes trends in SSDI awards all the more puzzling. We find secular increases in education attainment should work heavily against the aging of the population. While older individuals are more likely to have health-related work limitations, higher education opens up more work opportunities that may accommodate their limitations. It is further puzzling that the award rate at the vocational stage has doubled since the 1980s. Applications reaching this stage have been screened such that they are on the margin in terms of health and vocational related factors, crucially education, remain as the variables on which the award decision is conditioned. As education increases it is natural to expect the award rate conditional on reaching the vocational stage should fall and our analysis provides suggestive evidence supporting this hypothesis.

Our analysis frames important questions, but our methods have limitations that prevent us from finding answers. A key limitation of our analysis is that we were only supplied state-level data on vocational acceptances and denials for 2010-2015 from the SSA. This means that our inference on the correlation between demographics and the role of vocational consideration in the SSDI award process was limited to a potentially non-representative, recessionary, period. Complete data from state reports of Form 831 starting in the mid-1990s would allow a more accurate understanding of how demographic composition factors into SSDI outcomes. Further, we present correlations without a strong identification of causality. Recognizing these limitations, we present a cross-state analysis and discuss hypotheses to be undertaken in future work using appropriate methods. We find states with the highest application rates are concentrated in the South, Rust-Belt and Lower Midwest. Higher application rates are correlated with lower acceptance rates of applications reaching the vocational stage. This suggests researchers should both consider socio-economic and industrial characteristics common to these geographies as well as whether the implementation of SSA determination rules differs across regions and time.

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A Figures & Tables

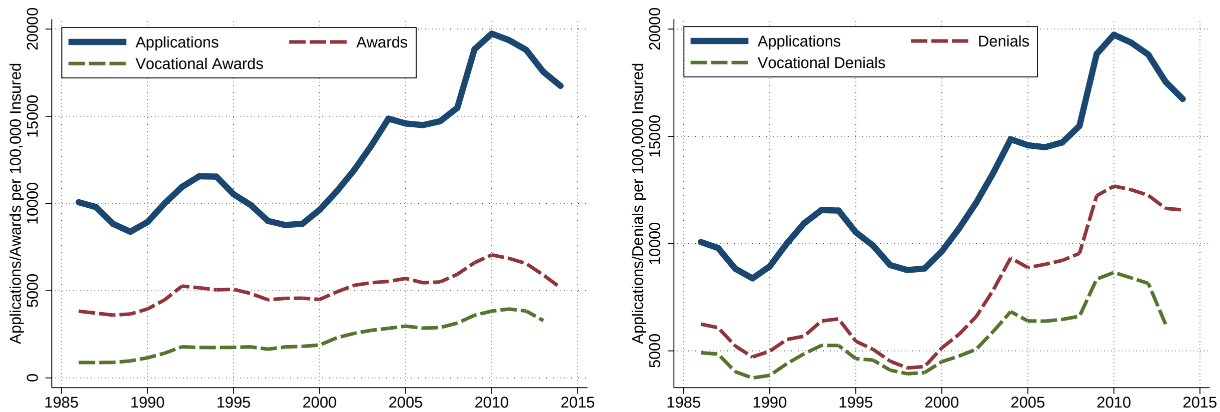

Figure 1: The contribution of vocational considerations to awards and denials. (Author's calculations from of Trustees (2000-2016) and data provided to author's by Social Security Advisory Board)

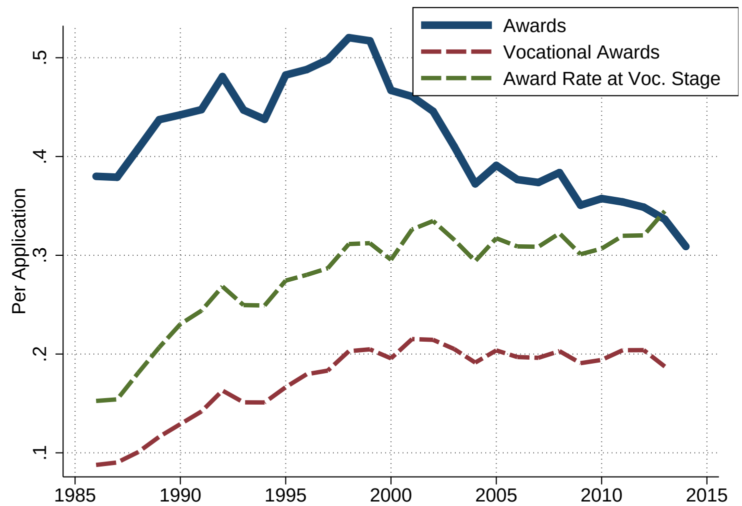

Figure 2: The contribution of vocational considerations to awards per application. (Author's calculations from of Trustees (2000-2016) and data provided to author's by Social Security Advisory Board)

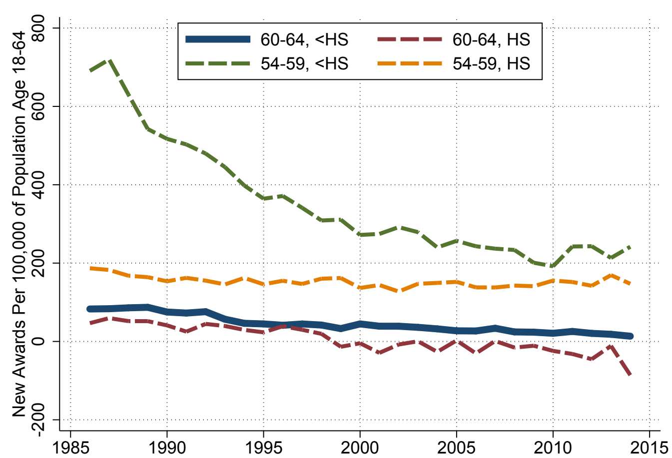

Figure 3: The contribution of age-education groups to vocational award trends.

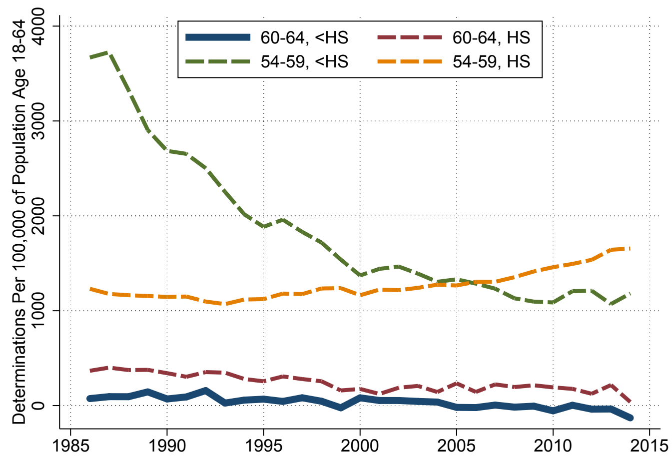

Figure 4: The contribution of disaggregated demographic groups to total determination trends.

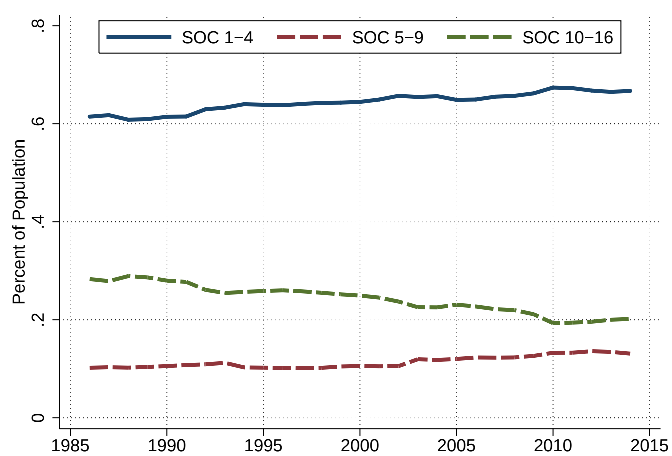

Figure 5: The population shares within each occupational grouping.

Table 1: SSA Determination Process

Factor	Description
Substantial Gainful Activity (SGA)	Max monthly earnings: $1,130 in 2016
SSDI Eligibility	Sufficient number of Social Security work credits
Medical Stage	Disability is determined to be severe and limit work
	• Can be mental and/or physical
	• Combination of non-severe impairments may be deemed severe
	SSA's Listing of Impairments
	• "meets" if is on the list
	• "equals" if limitation is equal to a listed impairment
	• result in award without considering vocational factors
Vocational Stage	Determination of applicant's Residual Functioning Capacity (RFC)
	• Tasks capable of despite impairments
	• ex: walking, standing, lifting
	• ex: understand, remember, and carry out instruction.
	Capable of past work as usually done in national economy
	• Considers significant work in past 15 years
	Capable of other work
	• Based on applicant's Maximum Sustained Capacity for Work

Table 2: Condensed Vocational Grid- Capability for Unskilled, Sedentary Work

Age	Education	Work Experience	Decision
50+	< High School	Unskilled	Disabled
	< High School	Skilled, not transferable	Disabled
	< High School	Skilled, transferable	Not Disabled
	High School or more	Unskilled	Disabled
	High School or more	Skilled, not transferable	Disabled
	High School or more	Skilled, transferable	Not Disabled
45-49	Illiterate/no English	Unskilled	Disabled
	< High School	Any	Not Disabled
	High School or more	Any	Not Disabled
18-44	Any	Any	Not Disabled

Full grid: Appendix 2 to Subpart P of Part 404 of Code of Federal Regulations
"Individuals approaching advanced age (age 50-54) may be significantly limited in vocational adaptability if they are restricted to sedentary work."

	Voc. acceptance	Voc. denial	Tot. applications	Tot. denial
	(1)	(2)	(3)	(4)
<HS, 60-65	1827	-2690	13248	8737
	(2755)	(7111)	(8095)	(6576)
<HS, 55-59	-4474	-3030	1096	2965
	(2730)	(7702)	(8794)	(6992)
HS, 60-65	2918***	2033	9628***	5858***
	(765)	(1959)	(2531)	(2046)
HS, 55-59	2222***	4366*	4307*	3368
	(668)	(2363)	(2560)	(2100)
>HS, 60-64	236	-464	681	828
	(278)	(657)	(797)	(633)
>HS, 55-59	-120	-1991***	-2704***	-2277***
	(268)	(730)	(829)	(668)
SOC 5-9, <HS, 60-65	-678	6510	-16595	-15927
	(3804)	(10480)	(11861)	(9681)
SOC 10-16, <HS, 60-65	744	8945	4423	6200
	(3564)	(9177)	(10855)	(8800)
SOC 5-9, HS, 60-65	-2200	356	-6356	-3458
	(1817)	(4782)	(6029)	(4746)
SOC 10-16, HS, 60-65	-3559***	-7609**	-8267*	-4996
	(1319)	(3336)	(4293)	(3387)
SOC 5-9, <HS, 55-59	5620	3075	14187	7609
	(3885)	(11990)	(11490)	(9181)
SOC 10-16, <HS, 55-59	6435**	18951**	31959***	25196***
	(3132)	(8910)	(10817)	(8564)
SOC 5-9, HS, 55-59	-672	-4846	2684	745
	(1448)	(4306)	(5157)	(4260)
SOC 10-16, HS, 55-59	-1194	3111	6872*	6345**
	(1024)	(3398)	(3776)	(3073)
Constant	76***	359***	584***	338***
	(17)	(52)	(57)	(45)
Observations	408	306	765	765
R^2	0.153	0.275	0.294	0.292

Standard errors in parentheses
* (p<0.10), ** (p<0.05), *** (p<0.01)

Table 3: The estimated effect of state-level demographic composition on acceptance and denial rates. Columns (1) and (2) estimate allowances and denials on vocational criteria. Columns (3) and (4) estimate total applications and denials.

Table 4: Contribution of Demographic Composition to SSDI Awards

	Marginal Effect of 1 Percentage Point Increase				Total Effect			
	Vocational:		Total:		Vocational:		Total:	
	Accept	Denial	Application	Denial	Accept	Denial	Application	Denial
55-59								
Total	2.79	-1.23	7.91	5.09	29.71	-13.09	84.31	54.24
less than HS	38.69	91.34	196.51	147.68	22.65	53.48	115.14	86.53
HS	4.84	22.35	49.16	39.40	15.32	70.79	155.74	124.81
60-64								
Total	1.37	-3.94	5.88	6.42	10.98	-31.91	47.22	51.66
less than HS	4.66	56.13	-12.11	-11.61	1.98	23.78	-5.09	-4.88
HS	-1.80	-13.90	6.99	5.18	-3.97	-30.21	14.96	11.11

Marginal Effects are the contribution per 100k WAP of shift of one percentage point away from the base group (workers age 18-54) to the group considered.
Total Effects are the marginal effect times the size of the percentage share of the demographic group in 2010-15.

Table 5: Contribution of Occupation Composition to SSDI Awards

	Marginal Effect of 1 Percentage Point Increase				Total Effect			
	Vocational:		Total:		Vocational:		Total:	
	Accept	Denial	Application	Denial	Accept	Denial	Application	Denial
55-59; <HS								
SOC 1-4	-44.74	-30.30	10.96	29.65	-5.55	-3.76	1.36	3.68
SOC 5-9	56.20	30.75	141.87	76.09	10.76	5.89	27.17	14.57
SOC 10-16	64.35	189.51	319.59	251.96	17.44	51.35	86.61	68.28
55-59; HS								
SOC 1-4	22.22	43.66	43.07	33.68	32.59	64.05	63.19	49.42
SOC 5-9	-6.72	-48.46	26.84	7.45	-3.90	-28.11	15.57	4.32
SOC 10-16	-11.94	31.11	68.72	63.45	-13.38	34.85	76.98	71.07
60-64; <HS								
SOC 1-4	18.27	-26.90	132.48	87.37	1.64	-2.42	11.90	7.85
SOC 5-9	-6.78	65.10	-165.95	-159.27	-1.02	9.84	-25.08	-24.07
SOC 10-16	7.44	89.45	44.23	62.00	1.36	16.36	8.09	11.34
60-64; HS								
SOC 1-4	29.18	20.33	96.28	58.58	30.29	21.10	99.93	60.80
SOC 5-9	-22.00	3.56	-63.56	-34.58	-9.53	1.54	-27.54	-14.99
SOC 10-16	-35.59	-76.09	-82.67	-49.96	-24.73	-52.86	-57.43	-34.71

Marginal Effects are the contribution per 100k WAP of shift of one percentage point away from the base group (workers age 18-54) to the group considered.
Total Effects are the marginal effect times the size of the percentage share of the demographic group in 2010-15.
SOC 1-4 are managerial, professional, sales, clerical, and administrative; SOC 5-9 are service & manual non-routine; SOC 10-16 are routine manual labor including agriculture, construction, and production.

Table 6: State Variation in Allowances

State	**Mean 2010-2015**				
	Determ.	Allow	Vocational Allow	Determ. at Voc Stage	% Allow of Voc Determ.
Alabama	1,673	515	325	60.0%	32.2%
Alaska	680	306	161	58.2%	42.7%
Arizona	720	199	85	54.7%	23.3%
Arkansas	1,618	513	304	59.0%	32.8%
California	706	233	123	57.7%	30.8%
Colorado	721	235	104	57.6%	24.7%
Connecticut	817	259	125	51.5%	29.6%
Delaware	984	354	183	61.5%	31.0%
D.C.	1,009	372	207	62.1%	33.7%

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Florida	1,172	341	171	60.6%	24.6%
Georgia	865	239	112	58.3%	21.0%
Hawaii	652	227	67	50.8%	20.5%
Idaho	1,011	340	195	60.2%	32.1%
Illinois	799	271	121	54.0%	28.5%
Indiana	1,216	397	176	55.8%	26.1%
Iowa	875	319	188	62.9%	33.7%
Kansas	684	251	117	57.6%	30.2%
Kentucky	1,495	410	238	64.2%	25.4%
Louisiana	1,192	441	246	56.4%	38.4%
Maine	1,137	369	185	53.6%	31.1%
Maryland	836	280	110	50.6%	25.9%
Massachusetts	936	384	220	56.0%	41.1%
Michigan	1,129	378	203	67.6%	29.5%
Minnesota	770	267	140	68.9%	26.2%
Mississippi	1,595	428	217	54.5%	25.3%
Missouri	1,378	489	267	54.8%	36.2%
Montana	857	312	164	65.7%	30.3%
Nebraska	798	302	170	64.7%	33.7%
Nevada	709	258	130	56.9%	32.7%
New Hampshire	994	484	241	54.8%	45.0%
New Jersey	830	368	225	59.5%	46.0%
New Mexico	734	255	135	57.7%	32.3%
New York	902	353	227	63.5%	40.2%
North Carolina	1,227	337	202	61.3%	27.6%
North Dakota	668	279	118	56.1%	32.3%
Ohio	1,085	375	205	63.9%	29.4%
Oklahoma	1,235	380	207	63.5%	26.5%
Oregon	973	323	200	63.6%	32.4%
Pennsylvania	1,074	373	228	65.5%	33.5%
Rhode Island	1,167	405	216	56.7%	33.3%
South Carolina	1,190	363	214	63.8%	28.7%
South Dakota	760	307	142	57.4%	33.1%
Tennessee	1,306	338	174	57.2%	23.8%
Texas	950	323	173	52.1%	35.2%
Utah	587	201	85	59.9%	24.2%
Vermont	977	402	233	63.1%	37.5%
Virginia	775	292	152	61.5%	32.9%
Washington	938	354	233	64.8%	39.6%
West Virginia	1,493	420	249	67.8%	23.9%
Wisconsin	822	299	134	63.0%	27.9%

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Wyoming	647	338	194	61.6%	50.4%
Total	988	338	181	59.5%	31.5%
Std. Deviation	293.3	85.3	60.3	5.58	6.86

Per 100,000 aged 18-64 population

Table 7: Predicted Allowances

State	**Vocational Allowances**	**Predicted Vocational Allowances**		
		Allow Rate at Voc. Stage	Determ. at Voc. Stage	Total Determ
Alabama	325	189	187	314
Alaska	161	251	181	128
Arizona	85	137	170	135
Arkansas	304	192	184	304
California	123	181	180	133
Colorado	104	145	179	135
Connecticut	125	174	160	153
Delaware	183	182	192	185
D.C.	207	198	193	189
Florida	171	144	189	220
Georgia	112	123	182	162
Hawaii	67	120	158	122
Idaho	195	188	188	190
Illinois	121	167	168	150
Indiana	176	154	174	228
Iowa	188	198	196	164
Kansas	117	178	179	128
Kentucky	238	149	200	281
Louisiana	246	226	176	224
Maine	185	183	167	213
Maryland	110	152	158	157
Massachusetts	220	242	174	176
Michigan	203	173	211	212
Minnesota	140	154	215	145
Mississippi	217	149	170	299
Missouri	267	213	171	259
Montana	164	178	205	161

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Nebraska	170	198	202	150
Nevada	130	192	177	133
New Hampshire	241	265	171	187
New Jersey	225	271	185	156
New Mexico	135	190	180	138
New York	227	236	198	169
North Carolina	202	162	191	230
North Dakota	118	190	175	125
Ohio	205	173	199	204
Oklahoma	207	156	198	232
Oregon	200	191	198	183
Pennsylvania	228	197	204	202
Rhode Island	216	196	177	219
South Carolina	214	169	199	223
South Dakota	142	194	179	143
Tennessee	174	140	178	245
Texas	173	207	162	178
Utah	85	142	187	110
Vermont	233	220	197	183
Virginia	152	193	192	146
Washington	233	233	202	176
West Virginia	249	141	211	280
Wisconsin	134	164	196	154
Wyoming	194	296	192	122
Total	181	185	185	185
Std. Deviation	60.3	40.3	17.4	55.1

Per 100,000 aged 18-64 population

Table 8: Covariance Matrix- percent contribution to Vocational Awards variance.

	Total Determ	Determ w/ Voc Consider	% Determ w/ Voc Consider Accpeted
Total Determ	60.9%		
Determ w/ Voc Consider	6.2%	6.9%	
Determ w/ Voc Consider accepted	-8.1%	-1.0%	35.2%

Table 9: Correlation Matrix

	Total Determ	Determ w/ Voc Consider	% Determ w/ Voc Consider Allowed
Total Determ	1		
Determ w/ Voc Consider	0.1512	1	
Determ w/ Voc Consider Allowed	-0.0872	-0.341	1

Supplemental Appendices

B Dataset Construction

Social Security Advisory Board Chartbook (accessed 9/14/2016). National-level time series (1985-2012) of the following variables: Total DI applications, awards, awards per insured population, initial denials by basis for decision, and initial acceptances by basis for decision. From `http://www.ssab.gov/Disability-Chartbook-Index/`

Social Security Advisory Board By direct correspondence provided us with state-level data on initial denials by basis for decision and initial acceptances by basis for decision for select years spanning 1998-2003, 2010-2013.

Social Security Administration By Freedom of Information Act request, provided us directly with state-level counts of awards and denials by basis of decision for FY 2014 and 2015.

Current Population Survey University of Minnesota's IPUMS-CPS database was used to generate state and national level demographic and occupation related variables from 1980-2015.

B.1 Dependent Variable Construction

The four dependent variables are all expressed as the number of incidents per 100,000 individuals in a state's working-age-population (18-64). The working-age-population itself is estimated from CPS data using person-level weights (wtsupp) and adjusting for the 2014 ASEC sample.

Vocational Allowances per 100k Working-Age-Population at the state level we have the total number of allowances from 2001-2015. We obtain the total number of allowances made at the vocational stage by multiplying the total allowances by the fraction that are made at the vocational stage, which we have for the following years: 2001-2003, 2010, and 2012-2015. Finally the number of vocational allowances is expressed in terms of allowances per 100,000 in the states' working-age-population.

Vocational Denials per 100k Working-Age-Population at the state level we have the total number of denials from 2001-2015. We obtain the total number of denials made at the vocational stage by multiplying the total denials by the fraction that are made at the vocational stage, which we have for the following years: 2003-2004, 2010, 2012-2013, and 2015. Finally the number of vocational denials is expressed in terms of denials per 100,000 in the states' working-age-population.

Total Allowances per 100k Working-Age-Population at the state level we have the total number of allowances from 2001-2015. The number of total allowances is expressed in terms of allowances per 100,000 in the states' working-age-population.

Total Denials per 100k Working-Age-Population at the state level we have the total number of denials from 2001-2015. The number of total denials is expressed in terms of denials per 100,000 in the states' working-age-population.

B.2 Independent Variable Construction

The independent variables used in this paper divide people by (1) age, (2) education, and (3) occupation. Individuals are grouped according to their age. Bins were chosen to be consistent with the age related guidelines in the vocational grid: 18-44, 45-54, 55-59, 60-65. We assign individuals into one of three education bins:

Less than High School includes all individuals that did not *complete* the 12th grade.

High School includes all individuals that completed the 12th grade.

More than High School includes all individuals that complete at least some college.

The education and age bins are combined to generate 12, mutually exclusive, education-age cells (Jaeger (1997)).

The CPS contains information regarding an individual's occupation classification following the Census Bureau's 1990 occupational classification scheme (occ90). We aggregate occupational classifications by assigning each individual to one of sixteen occupational bins consistent with the Standard Occupational Classification (SOC) scheme developed by the Bureau of Labor Statistics:

SOC 1 Managerial (002<occ90<38)

SOC 2 Professional (042<occ90<236)

SOC 3 Sales (242<occ90<286)

SOC 4 Clerical, admin (302<occ90<390)

SOC 5 Service: clean/maint (402<occ90<408)

SOC 6 Service: protect (412<occ90<428)

SOC 7 Service: food (432<occ90<445)

SOC 8 Service: health (444<occ90<448)

SOC 9 Service: personal (447<occ90<470)

SOC 10 Farm, fish, forest (472<occ90<500)

SOC 11 Mechanics (502<occ90<550)

SOC 12 Construction/extractors (552<occ90<618)

SOC 13 Precision production (632<occ90<700)

SOC 14 Operators: machine (702<occ90<800)

SOC 15 Operators: transport (802<occ90<860)

SOC 16 Operators: handlers (862<occ90<890)

We further consolidate occupational classifications into three groups: (1) SOC 1-4, (2) SOC 5-9, and (3) 10-16. The occupations were grouped according to their similarity in daily activities on the job. The first grouping contains occupations in which cognitively intensive tasks must be performed. The second group contains service jobs that require non-routine but manual work. The third and final group contains occupations in which the majority of tasks being performs ar routine and manual. The type of tasks necessary to work in an occupation are taken into consideration when determining a SSDI applicant's "maximum sustained work capability", and ultimately their allowance or denial status at the vocational stage. This grouping scheme is similar to those employed by Autor et al. (2003).

We cross the three occupational bins with the age and education bins to create 36, mutually exclusive, occupation-education-age bins. Once an individual is assigned to their respective demographic and occupational bins the sample is collapsed to form a state-level panel using person-level weights (wtsupp). State-level demographic and occupational variables represent the share of a state's working-age-population meeting the bins' conditions.

At the national level we follow the same procedure above to construct occupational bins; however, we clean the micro-data on wages, weeks worked in the past year, and usual hours worked per year before aggregating to the national level. We omit all observations in which an individual worked fewer than 50 weeks in the past year, usually worked fewer than 30 hours per week, and/or made less than $7,000 (in 2000$) (which approximates the annual earnings of a minimum wage, full-time, employee in 2000). We further exclude the self-employed and military personnel. We aggregate to the national level using person-level weights (wtsupp).

Two alternative SOC groupings were considered for robustness purposes. The first sorted occupations according to the national growth or decay of occupation's share of total employment from 1990-2015: (1) growth SOC 1,2,7, and 8, (2) stable SOC 3,5,6,9,10, and 15, and (3) decay SOC 4,11,12,13,14, and 16. The second grouping sorted occupation according to the share of workers in that occupational category with more than a high school education: (1) high education SOC 1-4, (2) moderate education SOC 7,9,11,12,14, and 15, and (3) low education SOC 5,6,8,10,13, and 16. Regardless of which grouping is used, the qualitative results regarding demographics remains un-changed. Our preferred grouping performs moderately better in terms of fit (adjusted r-squared). This is not surprising when using DI determinations as our dependent variable which have more to do with a worker's ability to perform work similar to past jobs or to be retrained for other available jobs in the economy than it does with the health of an occupation at the national level or an individuals level of formal schooling.

C Prediction of the Aggregate Trend

Aggregate trends in each (i) vocational awards per insured; and (ii) conditional vocational award rates; were predicted as follows:

- **Actual Trends**. Calculated directly from reported data.

- **Predicted by change in age structure alone**. For each age-sex cell, calculate the share in each education group for the time period 1985-89. Mathematically, for each a, s, e:

  $$\mu_e(a,s) = \sum_{t=1985}^{1989} \left(\frac{\pi_{a,e,s}}{\sum_e \pi_{a,e,s}(t)}/5\right)$$

  Re-weight the time series of cells to keep education shares within age-sex groups fixed, for $t = 1990-$:

  $$\hat{\pi}_{a,e,s}(t) = \pi_{a,e,s}(t) * \frac{\mu_e(a,s)}{\sum_e \pi_{a,e,s}(t)}$$

  Project time series by multiplying the estimated contribution $\beta_{a,e,s}$ of each cell a, e, s to the time series by the education-constant adjusted weights $\hat{\pi}_{a,e,s}(t)$ and sum over the cells. Next solve for a constant factor γ such that when we rerun the previous with $\gamma\beta_{a,e,s}$, we exactly match the average 1985-89 aggregates.

  $$\hat{T}(t) = \sum_{a,e,s} \gamma\beta_{a,e,s}\hat{\pi}_{a,e,s}(t)$$

- **Predicted by change in age and education**. Repeat the above procedure, but replace $\hat{\pi}_{a,e,s}(t)$ with the actual cell shares $\pi_{a,e,s}(t)$.

$$\hat{T}(t) = \sum_{a,e,s} \gamma \beta_{a,e,s} \pi_{a,e,s}(t)$$

- **Predicted by occupation trends applied evenly to all groups, fixed at 1985-89**. Calculate the average occupational shares in the national economy at each education level in 1985-89 as λ_e^j for occupation j. Calculate the contribution of changing occupational structure at time t as: $\delta_e(t) = \sum_j \lambda_e^j \beta_j \Delta_e^j(t-5, t+5)$; where β_j are coefficients from the state-panel regression and $\Delta_e^j(t-5, t+5)$ is a 10-year moving average of change in occupational share for education group e.

$$\hat{T}(t) = \sum_{a,e,s} \delta_e(t) \gamma \beta_{a,e,s} \pi_{a,e,s}(t)$$

- **Predicted by occupation trends applied according to occupation experience in each cell, fixed at 1985-89**. Calculate the average occupational shares in the national economy at each cell level in 1985-89 as $\lambda_{a,e,s}^j$ for occupation j. Calculate the contribution of changing occupational structure at time t as: $\delta_{a,e,s}(t) = \sum_j \lambda_{a,e,s}^j \beta_j \Delta_e^j(t-5, t+5)$; where β_j are coefficients from the state-panel regression and $\Delta_e^j(t-5, t+5)$ is a 10-year moving average of change in occupational share for education group e.

$$\hat{T}(t) = \sum_{a,e,s} \delta_{a,e,s}(t) \gamma \beta_{a,e,s} \pi_{a,e,s}(t)$$

- **Predicted by occupation trends applied according to actual occupation experience in each cell**. Calculate the average occupational shares in the national economy at each cell level across time as $\lambda_{a,e,s}^j(t)$ for occupation j. Calculate the contribution of changing occupational structure at time t as: $\delta_{a,e,s}(t) =$

$\sum_j \lambda^j_{a,e,s}(t)\beta_j\Delta^j_e(t-5,t+5)$; where β_j are coefficients from the state-panel regression and $\Delta^j_e(t-5,t+5)$ is a 10-year moving average of change in occupational share for education group e.

$$\hat{T}(t) = \sum_{a,e,s} \delta_{a,e,s}(t)\gamma\beta_{a,e,s}\pi_{a,e,s}(t)$$