Local Labor Market Conditions and the Transition Out of Unemployment: The Importance of Prior-Industry Demand

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Abstract

Most research investigating the effects of local labor market conditions on unemployment summarize those conditions in the form of Bartik's (1991) index. Such studies overlook an important component of local demand conditions, namely, the fortunes in workers' prior industries. This paper examines the effects of local own- and other-industry labor demand on the probability that jobseekers exit unemployment. To the extent that workers are tied to their prior lines of production, it becomes useful to distinguish between labor demand in their previous industry and the level of aggregate labor demand for their locale. After combining several U.S. datasets spanning the years 2003-2015, I find that a 10-percentage point increase in labor demand within an individual's prior local industry increases the probability of exiting unemployment by 2.7-percentage points after controlling for aggregate demand. Moreover, I document that the magnitude of this effect increases with a jobseeker's age and level of educational attainment. These findings suggest that, in addition to overall labor market conditions, prior-industry demand is an important determinant of unemployment transitions.

1. Introduction

Economists have shown that local labor demand shocks have significant consequences for labor market outcomes. For example, Holzer (1991) presents evidence suggesting that firm-level adjustments to employment and wages are largely explained by fluctuations in local labor demand. Blanchard and Katz (1992) describe how adverse state-level employment shocks affect unemployment, wages, and migration patterns. Additionally, this strand of literature has made apparent the effectiveness of labor demand in reducing joblessness, particularly when local unemployment is relatively high (Bartik 2014). These studies, and others, typically measure the strength of local aggregate demand using an index developed by Bartik (1991), which is equal to the local employment share weighted sum of national industry growth rates. In this sense, they show that the job prospects of the unemployed depend on the industrial composition of labor demand.

Implicit in such approaches is the notion that worker fortunes in a locale are independent of prior-industry demand, holding constant the level of local aggregate demand as measured by the demand index.[1] Thus, a worker displaced from, say, the steel industry, is presumed to face the same demand conditions as a worker displaced from the retail trade industry. However, a substantial literature has arisen demonstrating the importance of firm, industry, and occupation-specific human capital. This literature finds that laid off workers who find new employment arrangements tend to suffer earnings losses when they switch firms, industries, and occupations (Neal 1995). Recent work has also noted the importance of industry as more than a proxy for basic skills, as workers often have knowledge about products than cannot be transferred to other industries (Poletaev 2008). The notion that workers make substantial specific investments over the course of their working lives suggests that jobseekers who are fortunate enough to live in a locale with relatively strong labor

[1] A certain amount of heterogeneity is incorporated by estimating models for different demographic groups, or constructing demographic-group-specific indexes using demographic-group specific employment shares.

demand in their prior industry may find superior wage offers, and in turn have a reduced incentive for continued search.

This paper sheds new light on the impact of local conditions on worker transitions out of unemployment. In particular, I investigate whether otherwise identical jobseekers face different probabilities of exiting unemployment depending on the labor demand within their previous industries. I test this hypothesis by combining longitudinally linked Current Population Survey (CPS) records with employment data from the Bureau of Labor Statistics (BLS) covering the years 2003-2015. These data allow me to examine month-ahead labor market transitions as a function of local demand conditions, along with a rich set of controls for other variables potentially affecting transitions.

I begin the analysis by presenting a multisector theoretical job search model a la Fallick (1993) to illustrate how the influence of prior-industry labor demand could differ from that of demand conditions within other industries. Insofar as workers are tied to their previous lines of production, they may optimally allocate a significant portion of their search intensity toward their previous industry. Figure 1 shows unemployment outflows calculated as month ahead transition rates. Over the years 2003-2015, it is clear that jobseekers are more likely to return to their previous industry relative to switching industries. Consequently, labor demand shocks within a worker's prior sector may lead to a disproportionately large change in the likelihood of exiting an unemployment spell. In contrast, improved job prospects in other sectors may have a relatively small impact on the probability of exiting unemployment.

In the empirical analysis, I deploy a binary probit model of whether jobseekers exit unemployment during the succeeding month as a function of prior-industry employment growth while holding local aggregate demand constant. Although I am unable to directly measure industry-specific tenure, it is possible to gain insight into the intensity of industrial attachment by using age as a proxy for potential experience in a worker's prior industry. Similarly, a worker's level of educational attainment is likely to be related to their accumulated industry-specific human capital. I argue that higher levels of education tend to be investments in less general forms of human capital. Therefore, I present separate estimates of the prior-industry demand effect by age and education. Finally, I consider competing exit risks with a multinomial probit model in which workers may return to their prior industry, transition into a new industry, or exit the labor force.

My estimation results suggest that, on average, a 10-percentage point increase in prior-industry labor demand raises the probability of exiting unemployment by 2.7-percentage points after controlling for local conditions. Moreover, the effect of prior-industry labor demand increases with age and educational attainment—evidence consistent with the notion that older, highly educated workers may possess a relatively large stock of industry-specific human capital. Results from the multinomial probit model show that prior-industry demand raises the probability that a worker returns to their most recent industry. The relationship between prior-industry demand and switching industries, however, is not statistically significant at conventional levels. Finally, I find evidence that improvements in prior-industry conditions reduces the probability of exiting the labor force.

As a robustness check, I construct an instrument using plausibly exogenous variation in industry labor demand based on an industry's employment growth in nearby states. This approach allows me to reduce potential endogeneity resulting from labor supply adjustments. For example, an increase in employment growth may be a result of state population adjustments rather than changes in labor demand. In addition, my procedure also addresses the possibility for measurement error in measures of industry employment growth. The estimated effects from the 2SLS model are slightly larger than their corresponding LPM estimates, but the results are consistent with my main findings.

This paper contributes to a large literature on the labor market consequences of industrial composition. As discussed above, Bartik has provided several studies on the role of local demand in reducing unemployment and poverty for different demographic groups (Bartik 1991, 1996, 2014). Other researchers have highlighted the relationship between industry-level employment dynamics and unemployment. Simon (1988) documents that cities with higher industrial diversity, as measured by a Herfindahl index of employment shares, have lower rates of frictional unemployment. Neumann and Topel (1991) find that permanent changes in labor demand across sectors lead to temporary increases in unemployment. While these studies utilize measures of aggregate industrial composition, this article emphasizes the importance of jobseekers' prior local sectors.

In addition to contributing to the literature on local labor demand, this paper complements the work of Fallick (1993) who examines the role of own- and other-industry growth on the industrial mobility of displaced workers. An important difference between our studies is that I am able to examine prior-industry demand for all unemployed workers, instead of only using displaced workers. In addition, this study's use of longitudinally linked CPS records overcomes potential recall bias, which is often a concern for studies utilizing Displaced Workers Survey (DWS) data.

The remainder of this paper proceeds as follows. Section 2 presents a theoretical framework that incorporates industry-specific human capital into a job search model. Section 3 describes the data. Section 4 develops the statistical models. Section 5 presents the estimation results. Section 6 presents the robustness results. Section 7 concludes.

2. Theoretical Framework

When a worker becomes unemployed, they must decide how much effort to allocate towards their job search. Most job search models assume the existence of a single sector in which individuals' job prospects are influenced by the level of aggregate demand. This setup, however, is clearly inappropriate if one is interested in exploring changes in the industrial composition of labor demand. Since many economic models depend on basic job search theory, additional empirical work on the relationship between local labor market conditions and the unemployment exit hazard appears valuable.

In this section, I outline a multisector job search model following Fallick (1993) to examine the role of prior-industry labor demand on the hazard rate associated with exiting unemployment. I will show that there is a strong theoretical basis upon which to distinguish between industry-specific demands. In particular, the labor market conditions within distinct industries may not have equivalent effects of the job prospects of the unemployed.

Consider a simple economy with *J* industries. When individual *i* becomes unemployed they choose a level of search intensity, $s_j(t, X_i, h_{ij}) \in [0,1]$, to devote to finding a job in industry *j*. In this model, *t* represents the time period; X_i is a vector of individual characteristics; and h_{ij} is the level of industry-specific human capital for worker *i* in industry *j*. It is important to note that in my augmented version of Fallick's model, industry-specific human capital, h_{ij}, is broadly defined to represent a worker's attachment to their prior industry. Therefore h_{ij} may include items such as preferences for a particular industry or information that gives them an advantage in the job search process. The probability of finding an available job offer is given by:

$$\Gamma(t, X_i, h_{ij}) = \Gamma\left(s_j(t, X_i, h_{ij})\right) \tag{1}$$

Where $\Gamma(\cdot)$ is increasing and concave, with $\Gamma(0) = 0$ and $\Gamma(1) = 1$. Therefore, the probability of receiving a job offer from industry *j* in time period *t* is given by:

$$\pi_{i,j} = \alpha_j(t, X_i, h_{ij})\Gamma(t, X_i, h_{ij}) \tag{2}$$

Where $\alpha_j(t, X_i, h_{ij})$ is the probability of a worker receiving a job offer conditional on devoting all of their search effort to industry *j*, i.e. $s_j(t, X_i, h_{ij}) = 1$. The term $\alpha_j(t, X_i, h_{ij})$ may be thought of as the offer arrival rate within industry *j*. Finally, let $F_j(w_j^R(t, X_i, h_{ij}), X_i, h_{ij})$ represent the probability of receiving a wage offer of less than the reservation wage rate, $w_j^R(t, X_i, h_{ij})$.

In this setup, the probability that a jobseeker will transition from unemployment to employment in month t may be written as:

$$\lambda_{i,j}(t) = \alpha_j(t, X_i, h_{ij})\Gamma(t, X_i, h_{ij})[1 - F_j(w_j^R(t, X_i, h_{ij}), X_i, h_{ij})]. \tag{3}$$

In this model, workers consider their stock of industry-specific human capital, h_{ij}, before selecting their optimal level of search intensity. Consider the extreme case where a worker chooses to allocate their entire endowment of search effort to their prior industry. If this were the case, the above job search model implies that $\lambda_{i,k}(t) = 0 \; \forall \; k \neq j$. Hence, fluctuations in labor demand for other local industries do not affect the probability of reemployment. On the other hand, fluctuations in the employment growth rate of industry *j* affect the hazard function $\lambda_{i,j}(t)$ through changes in the wage-offer distribution, F_j, or the offer arrival rate, α_j.

Search theory does not provide a definitive prediction as to the sign of the prior-industry demand effect on $\lambda_{i,j}(t)$ since improving conditions in industry *j* may also increase the individual's reservation wage rate. However, it seems likely that an individual will choose to allocate more search effort to their previous industry if their industry-specific human capital improves their employment outcomes. To the extent this is true, the performance of an individual's previous industry may be an important and distinct determinant of their unemployment exit probability even after controlling for the effects of aggregate labor demand. The rest of this paper is devoted to testing this claim.

3. Data

The U.S. Census Bureau's Current Population Survey (CPS) provides monthly individual-level records on labor force status and the Census industry of most recent employment. Although the CPS is not a true panel, the use of longitudinally linked observations allows researchers to follow workers for up to a maximum of 16 months. Households remaining in the CPS for all rotations are surveyed for four months, ignored for eight months, and interviewed for an additional four months. This survey design allows for the construction of variables recording month-ahead unemployment transitions. Consequently, each individual may appear in my sample for a maximum of 6 months.[2]

A potential concern with using matched CPS data for modeling employment transitions is the existence of erroneous longitudinal linkages between individuals. In particular, two different individuals may be incorrectly assigned to the same unique identification number. I address this problem by removing observations for which there are obvious inconsistencies in age, race, or sex over time.[3] On the other hand, the CPS has the advantage of avoiding recall bias inherent in many panel datasets as respondents are interviewed every month (Evans 1995). For example, the DWS requires participants to recall events several years prior to the interview date. Another advantage of my dataset is the relatively large sample size, which allows for exploring effect heterogeneity across demographic groups.

I restrict my sample to respondents aged 18-64 who are unemployed for at least one month. To ensure that industry classification codes are consistent over time, the analysis uses data spanning the years 2003-2015—a time period using a common industrial classification scheme based on the 2000 Census. In addition, I do not include workers who are considered to be self-employed, unpaid

[2] Month-ahead transitions are available for 3 consecutive months in each of two 4-month rotations.
[3] In particular, an observation is deleted if the respondent reports ages that are greater than two years apart.

family workers, or those serving in the armed forces. Summary statistics for the full sample of individuals who experience at least one unemployment spell are displayed in the Table 1.

To estimate the probability that jobseekers exit a spell of unemployment, I further restrict the sample to individuals who are unemployed during the current month and have a record for labor market status in the following month. The unemployment spells are required to be a result of job loss from a private sector employer. Therefore, it is likely that my sample is mostly capturing involuntary separations. This choice is made to reduce the number of transitions that may be a result of voluntary job-to-job mobility. Table 2 presents summary statistics for the sample restricted to unemployed person-month observations.

Measures of industry-level labor demand are computed using employment data from the U.S. Bureau of Labor Statistics (BLS) State and Area Employment survey. CPS data are not used to measure industry labor demand as state-industry cell sizes are too small to produce reliable estimates. The BLS collects monthly data from a sample of establishments in all nonagricultural sectors. Since the employment data are classified according to the 2012 North American Industrial Classification System (NAICS), I construct a crosswalk that maps individuals in the CPS sample to their corresponding 2-digit NAICS sector. This procedure provides a total of 20 industry categories. Although a finer level of industry detail is available for the largest states, there are missing data issues for small states. Therefore, my analysis focuses on the 2-digit level of aggregation. Finally, state unemployment rate data come from BLS calculations of the official unemployment rate based on monthly CPS records.

4. Statistical Models

To begin the empirical analysis, I estimate a binary probit model to examine the effect of prior-industry and aggregate labor demand on the probability that an individual exits unemployment.

Each unemployed individual is observed in period *t* under particular labor market conditions that are hypothesized to influence their unemployment status in period *t+1*. This paper models the latent variable y^*, which represents the propensity to exit a spell of unemployment. It is assumed that an individual exits unemployment if y^* is strictly positive. Formally, the latent variable y^* is parameterized as

$$y_{ijst}^* = \boldsymbol{X_{ist}\beta} + \lambda DEMAND_{jst} + \boldsymbol{Z_{st}\alpha} + \omega_j + \phi_s + \psi_t + \nu_{ijst} \tag{4}$$

and

$$\begin{cases} y_{ijst} = 1 & \text{if } y_{ijst}^* > 0, \\ y_{ijst} = 0 & \text{if } y_{ijst}^* \leq 0. \end{cases}$$

y_{ijst} is an indicator variable for jobseeker *i*, in industry *j*, in state *s*, at time *t*. The variable y_{ijst} takes a value of unity if a jobseeker exits unemployment, and takes a value of zero otherwise.

The variable $DEMAND_{jst}$ is the 3-month ahead employment growth rate of a worker's local prior-industry. Hence, the parameter of interest for the analysis is given by λ. The vector $\boldsymbol{X_{ist}}$ contains standard demographic variables: age, age squared, female, married, (female)x(married), four education level indicators, white, central city, and citizenship. I allow for a flexible baseline hazard by including 20 month-of-unemployment indicators. Few workers are unemployed for a period exceeding 20 months.

In my preferred specification, the vector $\boldsymbol{Z_{st}}$ includes the monthly unemployment rate and 3-month ahead employment growth rate for state *s* in month *t*. In an alternative specification, I use the Bartik index to control for local labor demand. The Bartik index is a local employment share weighted sum of national industry employment growth rates. Effectively, this index predicts local area employment growth by using differences in industrial composition across states. Since the Bartik index excludes own-state employment, it is a plausibly exogenous shifter of labor demand. Following the literature, I compute the Bartik index as

$$BARTIK_{s,t} = \sum_{j=1}^{J} \theta_{j,s,t} g_{j,-s,t}$$

$$\sum_{j=1}^{J} \theta_{j,s,t} = 1.$$

The variable $\theta_{j,s,t}$ is the employment share of industry *j*, in state *s*, during month *t*. The variable $g_{j,-s,t}$ is the 3-month ahead national employment growth rate of industry *j*, excluding employment in state *s*, during month *t*. Due to data restrictions on smaller state industries, I am limited to using 38 states when including this control into any statistical model. For other specifications, I include all 48 contiguous states plus D.C.

The terms ω_j, ϕ_s, and ψ_t are industry, state, and date (month-year) indicators, respectively. The variable ν_{ijst} is an error term following a normal distribution with mean zero and standard deviation, σ. The probability that a jobseeker exits a spell of unemployment is given by

$$Prob(y_{ijst} = 1 \mid \boldsymbol{\gamma}) = \boldsymbol{\Phi}\left(\frac{\boldsymbol{\gamma}'\boldsymbol{\theta}}{\sigma}\right) \tag{5}$$

where $\boldsymbol{\gamma}$ represents a vector of all covariates included in the probability model. $\boldsymbol{\Phi}(\cdot)$ is the normal distribution function. The object $\boldsymbol{\theta}$ represents a vector of parameters, and σ is normalized to unity.

Although estimation of binary probit models provides the main results of the paper, the estimates do not reveal where unemployed workers wind up following a job separation. For example, some jobseekers may be reemployed in their prior industries, while others may exit the labor force entirely. Consequently, I also estimate a multinomial probit model (MNP) to account for four possible alternatives: unemployment, prior-industry reemployment, other-industry reemployment, and labor force exits.

The MNP model is estimated using a latent variable analogue to equation (4). Formally, I specify the latent variable as

$$y^*_{imjst} = \boldsymbol{X_{ist}\beta_m} + \lambda_m DEMAND_{jst} + \boldsymbol{Z_{st}\alpha_m} + \omega_j + \phi_s + \psi_t + \nu_{imjst}. \quad (6)$$

In this setting, the latent variable y^*_{imjst} is specific to alternative *m*. In addition, the MNP model assumes that the errors, ν_{ijst}, follow a multivariate normal distribution and may be correlated across alternatives. The main advantage of the MNP model is its relaxation of the independence of irrelevant alternatives (IIA) assumption imposed by other discrete choice models. For example, the popular multinomial logit (MNL) model assumes that the outcomes are independent, which is likely to be inappropriate in the context of labor market transitions.

5. Estimation Results

5.1 Binary Choice Models

I report average marginal effects (AME) from the binary probit model in Table 4. In model (1), I control for both the unemployment rate and actual state employment growth. As an alternative specification, I estimate model (2) and include the commonly used Bartik index as a measure of local labor demand. It is clear that there is a positive and statistically significant relationship between prior-industry demand and the predicted probability of exiting unemployment. In particular, a 10-percentage point increase in my measure of prior-industry labor demand increases the probability of exiting unemployment by about 2.7-percentage points. In any given month, the probability that a jobseeker transitions out of unemployment in the following month is 0.36. To give a sense of the estimated magnitude, a one standard deviation increase, about 0.064, in prior-industry demand increases the predicted probability of an unemployment exit by about 1.7 percentage points.

It is important to note that during the 2007-09 Great Recession, there were substantial differences in industry employment growth rates depending on the output of the sector. Table 3 shows means and standard deviations of 3-month employment growth rates for state-level industries. It is clear that some industries such as utilities are not particular volatile in terms of employment growth. On the other hand, the construction industry's growth rate has a standard deviation of around 10 percentage points. In addition, recessions appear to reduce employment in goods producing industries more severely relative to service providing industries. At the state-level, some Construction and Manufacturing sectors experienced 3-month employment declines well in excess of 10%. In contrast, a few local industries within the Health Care and Social Assistance exhibited growth rates exceeding 10%. These estimation results, when considered in the context of economic downturns, provide insight on the potentially severe labor market consequences of large-scale job destruction concentrated within particular industries.

Turning to the standard demographic variables, we can see that all categories of education have negative effects relative to the omitted education category of Less Than High School. Living in a central city has a small negative effect on exiting unemployment; however, it is not statistically significant at conventional levels. Finally, being a U.S. citizen has a large negative impact on leaving unemployment relative to jobseekers without U.S. citizenship.

To ensure that the relationship between prior-industry demand and the transition out of unemployment is not merely a result of aggregate business cycle fluctuations, the specification includes several controls to account for shifts in local aggregate demand. Although local unemployment and employment growth rates influence unemployment transitions, the inclusion of these covariates does little to affect the estimated coefficient on prior-industry demand. This finding is noteworthy because workers who are displaced in two different labor markets with similar levels of aggregate demand may experience significant disparities in job finding rates depending on the state of their previous industry.

While the initial results are revealing, it is unclear how shifts in industry demand affect different groups of workers. To the extent that industry-specific human capital is driving the relationship of interest, we might expect older workers with more potential industry experience to be particularly sensitive to the demand conditions within their previous sector. At the extreme, prior-industry demand may have little effect on the youngest workers who possess limited industry experience. Intuitively, there may be less of a penalty for switching industries if a worker is relatively inexperienced.

Marginal effect estimates at sample means from the probit specification for different age groups are reported in Table 5. The results from estimating the model across different age groups are striking. For the youngest job seekers, ages 18-24, the effect of prior-industry demand on the probability of exiting unemployment is small and statistically insignificant. However, the estimates marginal effect increases with age—with the exception of the 45-54 age group which is similar in magnitude to the 35-44 age group. The oldest jobseekers are the most sensitive to fluctuations in industry demand. For jobseekers 55-64 years old, a 10-percentage point increase in demand is associated with an increased exit probability of 3.8 percentage points, a significant difference relative to the youngest job seekers.

In terms of formal training, workers with higher levels of education may be more likely to have knowledge and skills tied to a particular field. With few exceptions, individuals with high school as their highest level of education are likely to have accumulated general human capital that prepares them to specialize in various industries. On the other hand, workers with a bachelor's or graduate degree specialize in a major field of study that may be better suited to a single industry. Therefore, we might expect more specialized workers to be particularly sensitive to industry demand shocks.

Table 6 presents marginal effect estimates for major education group subsamples. There is little difference in the own-industry effects for jobseekers with some college or less. This is consistent with an environment in which high schools and two-year education programs may be more focused on training workers with general skills. In marked contrast, I find a larger effect for college educated (BA or higher) jobseekers, with graduate degree holders having the highest estimated AME. For individuals with a graduate degree, a 10-percentage point increase in own-industry demand increases the probability of exiting unemployment by 4.2 percentage points. Due to the imprecision associated with the estimates, only graduate degree holders and those with less than high school have significant differences in demand effects.

My results add a new dimension to previous work on the interaction between education and unemployment. There is strong evidence that highly educated workers suffer a lower risk of unemployment and that additional education increases the rate of reemployment (Mincer 1991; Riddell and Song 2011). Interestingly, my findings suggest that conditional on becoming unemployed, highly educated workers may be more vulnerable to industry-level demand shocks. Therefore, although additional education reduces the overall risk of unemployment, it may also make workers more dependent on their chosen industry for employment opportunities. This seems to be a promising avenue for future research.

5.2 Multinomial Probit (MNP) Models

Results from the MNP model are presented in Table 8. I report the estimated marginal effects of prior-industry demand at sample means for each type of unemployment transition: unemployment, prior-industry, other-industry, and not in labor force. The base outcome for the model is that the jobseeker remains in unemployment during the next month. In addition, estimates of the unconditional transition probabilities are provided in Table 9.

The largest marginal effect is with respect to reemployment in one's prior-industry. It is useful to compare the marginal effect estimates to the unconditional transition probabilities. In particular, the probability of an unemployed individual returning to their previous industry is 0.12. And according to the MNP estimates, a 10-percentage point increase in own-industry labor demand raises the probability of own-industry reemployment by 0.025. Therefore, the demand effect appears to be one of an economically meaningful magnitude—especially considering the sharp reductions in local industry employment that are typically seen during recessionary episodes.

The impact of previous industry demand on the probability of becoming reemployed in a different industry is close to zero. This implies that most of the change in terms of the unemployment exit hazard is due to individuals returning to their old industries rather than joining other, possibly related, industries. This result is surprising because deteriorating conditions in a worker's prior industry might lead them to search for work in other sectors. The fact that there is little evidence of such substitution suggests that workers have strong attachments to their chosen industries.

Finally, stronger labor demand in a jobseeker's prior industry reduces the probability of exiting the labor force. A 10-percentage point increase in prior-industry demand reduces the probability of a labor force exit by 0.5 percentage points on a base of 14.3 percent. Therefore, considering the distribution of labor demand across industries, in addition to aggregate demand, may help explain why some individuals stop looking for work following a separation.

6. Robustness Checks

Studies examining the impact of local shocks often use different measures of local labor demand. So far, the results have been estimated using the 3-month employment growth rate of a worker's previous local industry. One potential issue is that the level of employment is an equilibrium quantity that is influenced by labor demand and labor supply. Consequently, it is possible that some of the estimated relationship is due to shifts in the supply of workers to an industry. In addition, if there is measurement error in the employment growth rates within particular sectors it is possible that my estimated marginal effects are biased towards zero. Using a valid instrumental variables approach can help address both of these concerns.

It is useful to consider an alternative measure designed to capture exogenous shocks to local industry labor demand. I develop an instrument that predicts the growth rate of a worker's previous industry based on employment changes in the same industry for other states within the same region. Formally, my instrument for labor demand is defined as

$$\widehat{DEMAND}_{j,s,t} = \frac{\sum_{i \in R_{-s}} e_{j,i,t+3}}{\sum_{i \in R_{-s}} e_{j,i,t}} - 1 \tag{7}$$

Where,

$e_{j,i,t}$ is the total employment level in industry *j*, in state *s*, during month *t*.

R_{-s} is the Census region for state *s* that excludes state *s*.

By construction, the labor demand instrument is not affected by changes in own-state population or labor supply adjustments. Moreover, it is assumed that employment growth for an industry within the same Census region is, in part, driven by a common factor. Therefore, we can think of the instrument as capturing exogenous shifts in labor demand for industry j in state s at month t.

I estimate a 2SLS version of equation (4) by instrumenting for the 3-month ahead prior-industry employment growth rate. The 2SLS estimates for the full sample and by age group are displayed in Table 13. For comparisons, I provide LPM estimates without instruments in Tables 11 and 12. The estimated coefficient on Prior-Industry Demand is 0.332, somewhat larger than the OLS estimate of 0.283. We can observe the same positive relationship between age and the magnitude of the own-industry effect. The 2SLS coefficients are of slightly larger magnitude across all age groups relative to OLS, but they agree with the main findings in the previous section. Table 14 presents the 2SLS results for five levels of educational attainment. The magnitude of the prior-industry demand effect is smaller for jobseekers with lower levels of educational attainment.

Unlike the OLS results, however, the estimated coefficient is higher for high school graduates and those with some college relative to individuals with less than a high school education. Once again, we can see that those with a bachelor's degree or higher appear most sensitive to own-industry demand shocks. This is particularly the case for jobseekers with graduate degrees. For graduate degree holders, a 10-percentage point increase in prior-industry demand increases the probability of exiting unemployment by 7.18 percentage points.

These findings provide additional evidence for the importance of industry-specific labor demand in terms of worker transitions. Given that the predicted employment growth rate cannot be influenced by labor supply adjustments in a jobseeker's own-state, I conclude that the effects captured in the benchmark OLS and probit models are largely a result of demand side forces.

Additionally, it is worth noting that OLS estimates may slightly underestimate the magnitude of the industry demand effects.

7. Conclusion

The existing labor literature firmly establishes relationship between local labor demand shocks and labor market outcomes. In particular, numerous studies have examined how aggregate shocks affect employment and unemployment within state labor markets. Unfortunately, evidence on the impacts of such aggregate fluctuations does not tell us about the importance of industry-level demand conditions. This is important because two workers displaced from labor markets with identical levels of aggregate demand may face stark differences in job search outcomes. In this article, I distinguish between local own-industry demand and aggregate demand as two forces capable of explaining the likelihood of exiting unemployment. Indeed, I find that own-industry demand is an economically significant determinant of unemployment transitions and for some workers may be as important as the level of aggregate demand.

Workers who become separated from industries with relatively low labor demand are less likely to exit unemployment even after accounting for time-varying state labor market conditions. On average, a 10-percentage point increase in own-industry demand reduces the probability of exiting unemployment in the following month by 2.7-percentage points. This point estimate, however, hides a large degree of heterogeneity in the impact of demand on different groups of workers. My analysis reveals that older workers are the most vulnerable to own-industry demand shocks. For example, the estimated marginal effect of a 10-percentage point industry demand shock on the unemployment exit probability is 3.8 percentage points for workers 55-64 years of age. Furthermore, there is some evidence that the most educated workers are more vulnerable to prior-industry demand fluctuations relative to those without a high school diploma.

These estimates are consistent with an explanation in which workers accumulate industry-specific skills and knowledge that in turn make them more sensitive to the demand conditions prevailing within their previous sectors. It is important to note that I do not claim that these effects are solely driven by human capital accumulation as I do not directly measure industry tenure. Nevertheless, it is reasonable to expect that if industry-specific human capital increases with age and education that workers may be more sensitive to own-industry demand shocks. The results of my MNP model show that these effects are primarily explained by increasing the likelihood that an unemployed worker returns to her former industry. The MNP results also suggest that better own-industry conditions may encourage the unemployed to continue searching for work.

In addition to the primary findings, I follow a more conventional approach of using a Bartik style instrument to identify the effects of exogenous shocks to industry labor demand. The estimated marginal effects from the 2SLS procedure are consistent with the effects estimated using the LPM specifications. In most cases, the 2SLS estimated marginal effects were only slightly larger relative to the LPM results. These slight differences may reveal either attenuation bias from measurement error in the industry growth covariate or they may reflect the influence of local labor supply adjustments. The precise source of these deviations is beyond the scope of this paper.

The results show that the distribution of local labor demand, rather than solely the level of aggregate demand, is a significant factor in explaining unemployment transitions. More importantly, as discussed above these effects differ markedly by age and level of educational attainment. In terms of policy, my analysis suggests the importance of accounting for industry-specific demand in addition to overall local economic conditions. This paper, however, does not take up a cost-benefit analysis of such policies. Finally, more evidence on how own-industry demand effects other labor market outcomes seems to be a promising avenue for future work.

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Figure 1: Unemployment Outflows by Month-Ahead Outcome

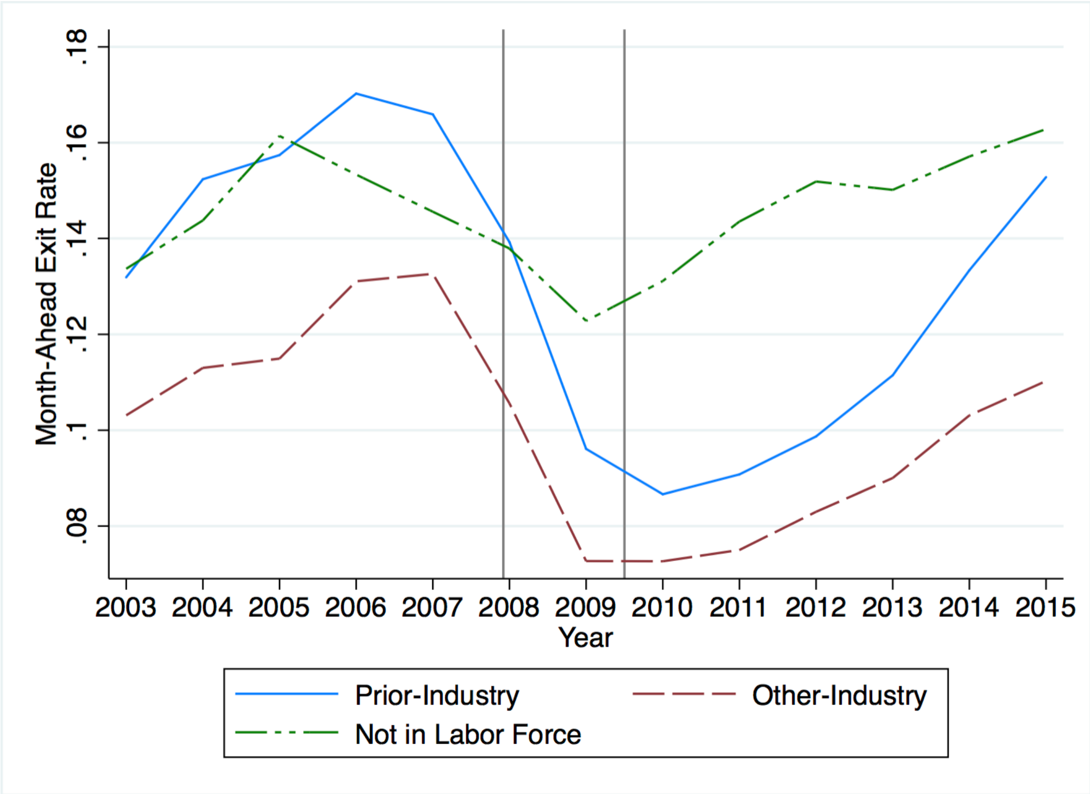

Table 1: Summary statistics for the respondents experiencing at least one month of unemployment

Variable	Obs.	Mean	Std. Dev.	Min	Max
Employed	1,353,484	0.372	0.483369	0	1
Unemployed	1,353,484	0.375	0.48425	0	1
NILF	1,353,484	0.252	0.434386	0	1
Age	1,353,484	35.856	13.31564	18	64
Female	1,353,484	0.477	0.499455	0	1
Married	1,353,484	0.384	0.486307	0	1
Female*Married	1,353,484	0.194	0.395713	0	1
White	1,353,484	0.733	0.442606	0	1
LTHS	1,353,484	0.174	0.379332	0	1
HS	1,353,484	0.352	0.477514	0	1
SC	1,353,484	0.303	0.459737	0	1
BA	1,353,484	0.126	0.332312	0	1
GD	1,353,484	0.044	0.205463	0	1
Central	1,353,484	0.303	0.459427	0	1
Citizenship	1,353,484	0.898	0.302241	0	1

Table 2: Sample of unemployed individuals with month-ahead labor market information

Variable	Obs.	Mean	Std. Dev.	Min	Max
Exit Next Month?	168753	0.354	0.478221	0	1
Age	168753	40.201	12.45436	18	64
Female	168753	0.397	0.489252	0	1
Married	168753	0.449	0.497357	0	1
Female*Married	168753	0.173	0.378234	0	1
White	168753	0.756	0.4295	0	1
LTHS	168753	0.150	0.357489	0	1
HS	168753	0.385	0.486695	0	1
SC	168753	0.285	0.451324	0	1
BA	168753	0.133	0.339938	0	1
GS	168753	0.046	0.20952	0	1
Central	168753	0.289	0.453438	0	1
Citizen	168753	0.915	0.278839	0	1
Months Unemployed	168753	6.439	7.23637	0	28.933

Table 3: Descriptive Statistics for State-Level Industries from 2003-2015

Industry Name	**Mean 3-Month Employment Growth Rate**	**Std. Dev.**	**Frequency**
Mining	0.0061	0.0783	1,264
Construction	0.0059	0.0969	7,426
Durable Goods	-0.0029	0.0211	7,584
Nondurable Goods	-0.0024	0.0236	7,584
Wholesale Trade	0.0010	0.0153	7,742
Retail Trade	0.0018	0.0322	7,742
Utilities	-0.0005	0.0184	6,320
Transportation and Warehousing	0.0037	0.0330	6,782
Information	-0.0037	0.0213	7,742
Finance and Insurance	0.0008	0.0101	7,426
Real Estate and Rental and Leasing	0.0016	0.0346	7,268
Professional, Scientific, and Technical Services	0.0052	0.0180	7,426
Management of Companies and Enterprises	0.0065	0.0225	6,892
Admin., Support, Waste Management, and Remediation	0.0066	0.0588	7,426
Educational Services	0.0129	0.1203	7,742
Health Care and Social Assistance	0.0056	0.0081	7,742
Arts, Entertainment, and Recreation	0.0214	0.1838	7,426
Accommodation and Food Services	0.0069	0.0641	7,426
Other Services	0.0018	0.0208	7,742
Government	0.0027	0.0583	7,742
All Industries	**0.0040**	**0.0637**	**142,444**

Table 4: Binary Probit Model Estimation Results

Dep. Var.: Exit Next Month? **Covariates**	Model 1	Model 2
Prior-Industry Demand	0.267***	0.286***
	(0.0219)	(0.0231)
Age	-0.0120***	-0.0120***
	(0.000844)	(0.000894)
Age_sq	0.000122***	0.000122***
	(0.0000105)	(0.0000112)
Female	0.0186***	0.0190***
	(0.00309)	(0.0030361)
Female x Married	0.0337***	0.0351***
	(0.00441)	(0.0046405)
Married	0.00899***	0.00751**
	(0.00346)	(0.0036872)
White	0.00780**	0.00697**
	(0.00328)	(0.00331)
Central	-0.000917	-0.000818
	(0.00403)	(0.00426)
Citizenship	-0.0762***	-0.0777***
	(0.00702)	(0.00727)
HS	-0.0217***	-0.0229***
	(0.00310)	(0.00329)
SC	-0.0250***	-0.0267***
	(0.00329)	(0.00339)
BA	-0.0484***	-0.0520***
	(0.00450)	(0.00449)
GD	-0.0548***	-0.0592***
	(0.00741)	(0.00684)
UR	-0.0155***	
	(0.00199)	
Local Demand	0.258*	
	(0.157)	
Bartik Index		-0.431
		(0.459)
State FE?	Yes	Yes
Time FE?	Yes	Yes
Industry FE?	Yes	Yes
Flexible Baseline Hazard?	Yes	Yes
Observations	162,322	143,830

Robust standard errors in parentheses (clustered by state)
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Binary Probit Model Results by Age Group

Dep. Var.: Exit Next Month? **Covariates**	18-24	25-34	35-44	45-54	55-64
Prior-Industry Demand	0.0763	0.234***	0.296***	0.276***	0.375***
	(0.0550)	(0.0462)	(0.0477)	(0.0436)	(0.0521)
UR	-0.0182***	-0.0152***	-0.0147***	-0.0170***	-0.0127***
	(0.00392)	(0.00237)	(0.00386)	(0.00337)	(0.00330)
Local Demand	0.475	0.336	0.372	0.187	0.0875
	(0.346)	(0.313)	(0.252)	(0.306)	(0.224)
Observations	20,086	35,897	38,063	41,160	27,116

Robust standard errors in parentheses (clustered by state)
*** p<0.01, ** p<0.05, * p<0.1

Dep. Var.: Exit Next Month? **Covariates**	18-24	25-34	35-44	45-54	55-64
Prior-Industry Demand	0.0431	0.253***	0.344***	0.290***	0.388***
	(0.0526)	(0.0476)	(0.0505)	(0.0497)	(0.0550)
Bartik Index	0.427	-0.728	-1.862**	-0.00539	0.245
	(0.992)	(0.779)	(0.835)	(1.0206)	(1.0628)
Observations	17,610	31,673	33,744	36,694	24,109

Robust standard errors in parentheses (clustered by state)
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Binary Probit Model Results by Education Level

Dep. Var.: Exit Next Month? **Covariates**	LTHS	HS	SC	BA	GD
Prior-Industry Demand	0.246***	0.219***	0.230***	0.322***	0.421***
	(0.0598)	(0.0331)	(0.0522)	(0.0624)	(0.0754)
UR	-0.0186***	-0.0182***	-0.0105***	-0.0135***	-0.0275***
	(0.00432)	(0.00230)	(0.00313)	(0.00380)	(0.00699)
Local Demand	0.289	0.627***	0.121	-0.175	-0.104
	(0.391)	(0.233)	(0.222)	(0.393)	(0.497)
Observations	23,730	63,101	46,250	21,646	7,595

Robust standard errors in parentheses (clustered by state)
*** p<0.01, ** p<0.05, * p<0.1

Dep. Var.: Exit Next Month? **Covariates**	LTHS	HS	SC	BA	GD
Prior-Industry Demand	0.274***	0.268***	0.215***	0.344***	0.394***
	(0.0565)	(0.0424)	(0.0555)	(0.0652)	(0.0812)
Bartik Index	-1.419	-0.143	-0.476	-0.818	0.714
	(0.890)	(0.577)	(0.725)	(2.377)	(2.583)
Observations	20,821	55,406	41,377	19,499	6,727

Robust standard errors in parentheses (clustered by state)
*** p<0.01, ** p<0.05, * p<0.1

Table 7: Unemployment Exit Rates by Education Group

Education Level	Mean(Exit Next Month?)	Std. Dev.	Freq.
LTHS	0.404	0.49061	24415
HS	0.359	0.47968	64678
SC	0.351	0.47726	47087
BA	0.319	0.46627	21894
GD	0.336	0.47236	7673
Total	**0.357**	**0.47910**	**165747**

Table 8: Multinomial Probit Model (MNP) Results by Transition Type

Outcome Next Month	Average Marginal Effect	Standard Error	P-value	95% CI Lower Bound	95% CI Upper Bound
Unemployment	-0.183	0.0224	0	-0.227	-0.139
Prior-Industry	0.248	0.0148	0	0.219	0.277
Other-Industry	-0.0129	0.0107	0.228	-0.0339	0.008
Not in Labor Force	-0.0526	0.0169	0.002	-0.0857	-0.0194

Table reports robust standard errors clustered by state

Table 9: Transition Probabilities for Unemployed Workers in Sample

Outcome Next Month?	Observations	Mean of Outcome Variable	Standard Deviation
Unemployed	165,747	0.647	0.478
Prior-Industry	165,747	0.119	0.323
Other-Industry	165,747	0.093	0.290
Not in Labor Force	165,747	0.143	0.350

Table 10: First Stage Estimates

Dep. Var.: Prior-Industry Demand **Covariates**	First Stage
Predicted Growth	0.984***
	(0.0145)
Age	4.23e-05
	(6.91e-05)
Age Squared	-5.37e-07
	(7.85e-07)
Female	-0.000409
	(0.000236)
Female*Married	0.000748**
	(0.000266)
Married	-8.42e-05
	(0.000235)
White	-0.000403
	(0.000347)
Central	-0.000160
	(0.000220)
Citizenship	0.000578
	(0.000461)
HS	0.000244
	(0.000144)
SC	-0.000415
	(0.000405)
BA	-0.000166
	(0.000396)
GD	-0.000393
	(0.000519)
UR	0.00142
	(0.00229)
UR Squared	-0.000144
	(0.000273)
UR Cubed	6.99e-06
	(1.19e-05)
Local Demand	0.926***
	(0.224)
Local Demand Squared	2.855
	(1.700)
Local Demand Cubed	78.38
	(61.53)
State FE?	Yes.
Time FE?	Yes.
Industry FE?	Yes.
Flexible Baseline Hazard?	Yes.
Constant	-0.0272**
	(0.0112)
Observations	162,298
R-squared	0.786

Robust standard errors in parentheses (clustered by industry)
*** p<0.01, ** p<0.05, * p<0.1

Table 11: LPM Estimates by Age Group

Dep. Var.: Exit Next Month? **Covariates**	(1) Full Sample	(2) 18-24	(3) 25-34	(4) 35-44	(5) 45-54	(6) 55-64
Prior-Industry Demand	0.283***	0.0773	0.244***	0.312***	0.299***	0.411***
	(0.0228)	(0.0547)	(0.0477)	(0.0495)	(0.0454)	(0.0545)
Age	-0.0126***	-0.187***	-0.0305*	-0.0416	0.0316	-0.150***
	(0.000864)	(0.0449)	(0.0172)	(0.0288)	(0.0293)	(0.0462)
Age Squared	0.000128***	0.00399***	0.000451	0.000513	-0.000330	0.00132***
	(1.07e-05)	(0.00106)	(0.000288)	(0.000365)	(0.000295)	(0.000392)
Female	0.0184***	0.0313***	0.0172***	0.0201**	0.0122*	0.000154
	(0.00308)	(0.00817)	(0.00599)	(0.00827)	(0.00671)	(0.00899)
Female x Married	0.0342***	0.0401*	0.0405***	0.0409***	0.0432***	0.0359***
	(0.00447)	(0.0221)	(0.0104)	(0.00984)	(0.00810)	(0.0108)
Married	0.00929***	-0.0227	0.00821	0.0152*	-0.00364	0.0209**
	(0.00338)	(0.0156)	(0.00735)	(0.00767)	(0.00605)	(0.00948)
White	0.00846**	0.0393***	0.0130**	-0.000953	-0.00311	-0.00164
	(0.00319)	(0.00886)	(0.00589)	(0.00568)	(0.00538)	(0.0121)
Central	-0.00100	0.0106	-0.00494	-0.00439	0.00117	0.000422
	(0.00403)	(0.00919)	(0.00795)	(0.00533)	(0.00719)	(0.00840)
Citizenship	-0.0795***	-0.126***	-0.104***	-0.0704***	-0.0552***	-0.0523***
	(0.00768)	(0.0167)	(0.0144)	(0.00833)	(0.0147)	(0.0175)
HS	-0.0225***	-0.00529	-0.0203**	-0.0231**	-0.0339***	-0.0221
	(0.00321)	(0.00676)	(0.00923)	(0.00879)	(0.00753)	(0.0132)
SC	-0.0255***	0.0467***	-0.0153*	-0.0438***	-0.0401***	-0.0399***
	(0.00337)	(0.0103)	(0.00833)	(0.00781)	(0.00824)	(0.0147)
BA	-0.0481***	0.0439**	-0.0240**	-0.0677***	-0.0623***	-0.0592***
	(0.00450)	(0.0206)	(0.0103)	(0.00980)	(0.00904)	(0.0152)
GD	-0.0545***	0.0276	-0.0165	-0.0661***	-0.0682***	-0.0676***
	(0.00699)	(0.0856)	(0.0144)	(0.0133)	(0.0114)	(0.0181)
UR	-0.0152***	-0.0183***	-0.0149***	-0.0143***	-0.0167***	-0.0122***
	(0.00197)	(0.00397)	(0.00239)	(0.00380)	(0.00339)	(0.00338)
Local Demand	0.258	0.495	0.335	0.368	0.194	0.0906
	(0.158)	(0.347)	(0.314)	(0.257)	(0.312)	(0.232)
State FE?	-0.00573***	-0.0318***	0.0234***	-0.00363	-0.0101**	-0.00775
Time FE?	(0.00187)	(0.00569)	(0.00463)	(0.00365)	(0.00385)	(0.00551)
Industry FE?	-0.00597***	-0.0490***	0.0305***	-0.00120	-0.0143***	-0.00408
Flexible Baseline Hazard?	(0.00200)	(0.00556)	(0.00390)	(0.00434)	(0.00408)	(0.00678)
Constant	0.681***	2.605***	0.923***	1.234**	-0.330	4.660***
	(0.0358)	(0.465)	(0.262)	(0.569)	(0.731)	(1.357)
Observations	162,322	20,086	35,897	38,063	41,160	27,116
R-squared	0.070	0.080	0.063	0.067	0.068	0.083

Robust standard errors in parentheses (clustered by state)
*** p<0.01, ** p<0.05, * p<0.1

Table 12: LPM Estimates by Educational Attainment

Dep. Var.: Exit Next Month? **Covariates**	(1) LTHS	(2) HS	(3) SC	(4) BA	(5) GD
Prior-Industry Demand	0.255***	0.227***	0.244***	0.356***	0.477***
	(0.0615)	(0.0340)	(0.0541)	(0.0681)	(0.0826)
Age	-0.0104***	-0.00991***	-0.0180***	-0.0213***	-0.0184***
	(0.00220)	(0.00104)	(0.00145)	(0.00239)	(0.00437)
Age Squared	0.000114***	0.000103***	0.000183***	0.000216***	0.000190***
	(2.90e-05)	(1.28e-05)	(1.75e-05)	(2.83e-05)	(4.71e-05)
Female	0.0279***	0.0192***	0.0121**	0.0203*	0.0128
	(0.00952)	(0.00574)	(0.00585)	(0.0115)	(0.0190)
Female x Married	0.0208	0.0276***	0.0205**	0.0457***	0.103***
	(0.0156)	(0.00828)	(0.00985)	(0.0134)	(0.0218)
Married	-0.00738	0.00561	0.0221***	0.0217**	-0.0122
	(0.00740)	(0.00509)	(0.00663)	(0.00974)	(0.0223)
White	0.0143	0.00415	0.00653	0.00936	0.0122
	(0.00916)	(0.00404)	(0.00683)	(0.0109)	(0.0141)
Central	0.00808	-0.00589	-0.000511	-0.00375	0.00308
	(0.00804)	(0.00652)	(0.00585)	(0.00700)	(0.0128)
Citizenship	-0.0957***	-0.0824***	-0.0794***	-0.0445**	-0.0103
	(0.0118)	(0.00884)	(0.0163)	(0.0199)	(0.0170)
UR	-0.0185***	-0.0180***	-0.00995***	-0.0132***	-0.0271***
	(0.00433)	(0.00236)	(0.00309)	(0.00387)	(0.00758)
Local Demand	0.268	0.640***	0.120	-0.160	-0.0890
	(0.391)	(0.235)	(0.225)	(0.395)	(0.521)
State FE?	Yes.	Yes.	Yes.	Yes.	Yes.
Time FE?	Yes.	Yes.	Yes.	Yes.	Yes.
Industry FE?	Yes.	Yes.	Yes.	Yes.	Yes.
Flexible Baseline Hazard?	Yes.	Yes.	Yes.	Yes.	Yes.
Constant	0.633***	0.639***	0.708***	0.755***	1.072***
	(0.0766)	(0.0362)	(0.0753)	(0.0694)	(0.172)
Observations	23,730	63,101	46,250	21,646	7,595
R-squared	0.071	0.061	0.075	0.099	0.145

Robust standard errors in parentheses (clustered by state)
*** p<0.01, ** p<0.05, * p<0.1

Table 13: 2SLS Estimates by Age Group

Dep. Var.: Exit Next Month? **Covariates**	(1) Full Sample	(2) 18-24	(3) 25-34	(4) 35-44	(5) 45-54	(6) 55-64
Prior-Industry Demand	0.332***	0.106*	0.327***	0.370***	0.334***	0.429***
	(0.0241)	(0.0581)	(0.0559)	(0.0550)	(0.0580)	(0.0642)
Age	-0.0126***	-0.187***	-0.0307*	-0.0413	0.0320	-0.149***
	(0.000852)	(0.0442)	(0.0169)	(0.0283)	(0.0289)	(0.0455)
Age Squared	0.000128***	0.00399***	0.000455	0.000510	-0.000334	0.00131***
	(1.06e-05)	(0.00105)	(0.000283)	(0.000359)	(0.000291)	(0.000385)
Female	0.0184***	0.0313***	0.0172***	0.0201**	0.0122*	0.000130
	(0.00304)	(0.00803)	(0.00593)	(0.00813)	(0.00662)	(0.00886)
Female x Married	0.0341***	0.0398*	0.0402***	0.0409***	0.0432***	0.0359***
	(0.00443)	(0.0217)	(0.0103)	(0.00965)	(0.00801)	(0.0106)
Married	0.00926***	-0.0227	0.00838	0.0151**	-0.00374	0.0208**
	(0.00334)	(0.0154)	(0.00723)	(0.00752)	(0.00599)	(0.00934)
White	0.00844***	0.0393***	0.0129**	-0.000875	-0.00317	-0.00166
	(0.00316)	(0.00871)	(0.00583)	(0.00560)	(0.00530)	(0.0119)
Central	-0.000967	0.0107	-0.00484	-0.00441	0.00119	0.000447
	(0.00397)	(0.00904)	(0.00782)	(0.00526)	(0.00710)	(0.00828)
Citizenship	-0.0796***	-0.126***	-0.104***	-0.0705***	-0.0552***	-0.0524***
	(0.00758)	(0.0164)	(0.0142)	(0.00819)	(0.0145)	(0.0172)
HS	-0.0224***	-0.00530	-0.0202**	-0.0229***	-0.0338***	-0.0221*
	(0.00315)	(0.00664)	(0.00911)	(0.00863)	(0.00740)	(0.0130)
SC	-0.0254***	0.0467***	-0.0151*	-0.0435***	-0.0399***	-0.0399***
	(0.00333)	(0.0101)	(0.00822)	(0.00770)	(0.00811)	(0.0145)
BA	-0.0480***	0.0437**	-0.0241**	-0.0675***	-0.0621***	-0.0591***
	(0.00444)	(0.0202)	(0.0102)	(0.00967)	(0.00889)	(0.0149)
GD	-0.0544***	0.0274	-0.0173	-0.0658***	-0.0682***	-0.0675***
	(0.00692)	(0.0842)	(0.0144)	(0.0130)	(0.0112)	(0.0179)
UR	-0.0152***	-0.0183***	-0.0148***	-0.0143***	-0.0167***	-0.0123***
	(0.00196)	(0.00390)	(0.00235)	(0.00375)	(0.00336)	(0.00330)
Local Demand	0.184	0.443	0.200	0.272	0.145	0.0659
	(0.155)	(0.349)	(0.305)	(0.257)	(0.317)	(0.230)
State FE?	Yes.	Yes.	Yes.	Yes.	Yes.	Yes.
Time FE?	Yes.	Yes.	Yes.	Yes.	Yes.	Yes.
Industry FE?	Yes.	Yes.	Yes.	Yes.	Yes.	Yes.
Flexible Baseline Hazard?	Yes.	Yes.	Yes.	Yes.	Yes.	Yes.
Constant	0.677***	2.603***	0.921***	1.228**	-0.346	4.627***
	(0.0366)	(0.458)	(0.260)	(0.559)	(0.720)	(1.333)
Observations	162,298	20,086	35,885	38,058	41,154	27,115
R-squared	0.070	0.080	0.062	0.067	0.068	0.083

Robust standard errors in parentheses (clustered by state)
*** p<0.01, ** p<0.05, * p<0.1

Table 14: 2SLS Estimates by Education Level

Dep. Var.: Exit Next Month? **Covariates**	(1) LTHS	(2) HS	(3) SC	(4) BA	(5) GD
Prior-Industry Demand	0.213***	0.280***	0.269***	0.406***	0.716***
	(0.0685)	(0.0387)	(0.0547)	(0.0787)	(0.116)
Age	-0.0104***	-0.00993***	-0.0180***	-0.0213***	-0.0184***
	(0.00217)	(0.00102)	(0.00143)	(0.00236)	(0.00429)
Age Squared	0.000114***	0.000103***	0.000183***	0.000216***	0.000190***
	(2.86e-05)	(1.25e-05)	(1.73e-05)	(2.79e-05)	(4.60e-05)
Female	0.0278***	0.0192***	0.0121**	0.0202*	0.0121
	(0.00937)	(0.00568)	(0.00578)	(0.0113)	(0.0187)
Female x Married	0.0208	0.0274***	0.0205**	0.0457***	0.103***
	(0.0153)	(0.00817)	(0.00972)	(0.0132)	(0.0215)
Married	-0.00765	0.00563	0.0221***	0.0216**	-0.0121
	(0.00733)	(0.00502)	(0.00654)	(0.00956)	(0.0217)
White	0.0145	0.00414	0.00650	0.00923	0.0121
	(0.00904)	(0.00399)	(0.00673)	(0.0107)	(0.0139)
Central	0.00786	-0.00582	-0.000472	-0.00368	0.00331
	(0.00791)	(0.00643)	(0.00576)	(0.00687)	(0.0125)
Citizenship	-0.0958***	-0.0826***	-0.0795***	-0.0446**	-0.0105
	(0.0116)	(0.00874)	(0.0160)	(0.0196)	(0.0165)
UR	-0.0184***	-0.0180***	-0.00995***	-0.0131***	-0.0275***
	(0.00426)	(0.00234)	(0.00305)	(0.00385)	(0.00728)
Local Demand	0.345	0.557**	0.0833	-0.212	-0.357
	(0.390)	(0.225)	(0.221)	(0.391)	(0.521)
State FE?	Yes.	Yes.	Yes.	Yes.	Yes.
Time FE?	Yes.	Yes.	Yes.	Yes.	Yes.
Industry FE?	Yes.	Yes.	Yes.	Yes.	Yes.
Flexible Baseline Hazard?	Yes.	Yes.	Yes.	Yes.	Yes.
Constant	0.603***	0.642***	0.707***	0.747***	1.073***
	(0.0711)	(0.0359)	(0.0757)	(0.0715)	(0.165)
Observations	23,724	63,087	46,247	21,645	7,595
R-squared	0.071	0.061	0.075	0.099	0.144

Robust standard errors in parentheses (clustered by state)
*** p<0.01, ** p<0.05, * p<0.1