The impact of spatial flexibility on unemployment duration in young college-educated workers

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1 – Introduction

A growing number of young people are seeking post-secondary education, with U.S. undergraduate college enrollment increasing from 10.5 million students in 1980 to 17.6 million in 2009 (Avery and Turner 2012). As college enrollment spikes, the cost of attending college is also observed to be climbing. Estimates suggest two-thirds of individuals graduating from public and private four-year colleges in the U.S. in 2011 had outstanding student loans, with debt among those individuals averaging nearly 27 thousand dollars (Reed and Cochrane 2012). Furthermore, the aggregate level of student loan debt is growing, with the current level projected at more than 1 trillion dollars.[1]

Hence, many young college graduates are experiencing the financial burden of substantial debt accumulation. At the same time, the labor market is presenting additional challenges to their financial solvency. Analysis reveals the recent economic crisis has worsened labor market outcomes in the United States. Specifically, Rothstein (2011) reports that non-farm payroll employment decreased by roughly 6.8 million from the midpoint of 2008 to that of 2009. These factors are likely to increase the importance that college-educated job market entrants place on their initial employment. Individuals with outstanding debt in a struggling economy may take unique steps to improve their labor market outcomes. One possible means of generating this type of job market opportunity is "spatial flexibility". Spatial flexibility is the act on the part of an individual to access labor markets outside of the one nearest by. It includes two overarching components, long distance commuting and migration (van Ham and Hooimeijer 2008). Regarding migration in particular, there is a precedent in economic theory for treating relocation from one spatially separate labor market to another as an investment (Sjaastad 1962). In the presence of economic incentives, individuals can be induced into relocation (Bowles 1970).

The goal of this study is to measure the impact of spatial flexibility on unemployment duration for young college graduates in the United States. In particular, we address a number of research questions. First, does spatial flexibility affect unemployment durations, and if so, how? Second, is this effect changed in any way by the recent global financial crisis? Finally, do any personal

[1] http://www.finaid.org/loans/studentloandebtclock.phtml

characteristics (socioeconomic, locational, etc.) change the way individuals experience the effect of spatial flexibility? We hypothesize that spatial flexibility will improve labor market experiences by shortening unemployment durations. We presume this impact will be redoubled after the onset of the financial crisis. Finally, we think a number of personal characteristics including race, gender, and marital status will affect unemployment durations in the presence of spatial flexibility.

The rest of this paper is organized as follows. First, we undertake a review of literature relevant to unemployment, and migration. Second, we introduce the methods we employ to analyze the impacts of spatial flexibility on unemployment duration. Third, we describe the data to be used in this analysis, including a discussion of the advantages and disadvantages of available datasets. Fourth, we report the results of our analysis. Finally, we make concluding remarks and attempt to shed light on possible policy implications of the results.

2 – Literature Review

2.1 – Background and Current State of Youth Unemployment

A considerable body of economics literature exists addressing the topic of youth unemployment and its determinants. At the outset of our survey of this literature, it is worth noting there is debate as to the definition of youth among the relevant studies. An International Labor Organization (2010) report on youth unemployment indicates two sources of this debate, namely differing definitions for statistical agencies across nations, as well as the tendency for young people to delay their job market entry in recent years. We give further attention to the issue of defining cutoffs for youth age groups in section 4 of this paper.

There is strong evidence justifying the importance of studying youth unemployment. Problems with youth unemployment at the individual level include potentially lifelong labor market inhibition and social exclusion. In the context of the economy at-large, young people lose out on income, which can have negative effects on savings and aggregate demand. Furthermore, institutional and governmental investments in education are squandered. Taken together, the economic detriments of youth unemployment constitute serious problems for societies (International Labor Organization 2010).

International Labor Organization data reveal unemployment rates for young people to be "perpetually higher" than those for adults, due to both supply and demand side labor market factors (International Labor Organization 2010).[2] The report estimates the 2009 global youth unemployment rate to be 13.0 percent, compared to 4.9 percent for adults. It additionally documents larger increases in the youth unemployment rate relative to adult rate associated with the early stages of the recent global recession. Between 2007 and 2009, the youth rate climbed 1.1 percentage points, compared to 0.7 percentage points for adults. Furthermore, in 2008 the global youth share of unemployment was 40.2 percent, despite the fact that youths comprised less than 25 percent of the world's total working-age population. As a final note, phenomena of disproportionate youth unemployment affect developed and developing nations alike. For developed economies in 2009, the ratio of youth-to-adult unemployment rates was 2.5, meaning in these regions youths were around two-and-a-half times as likely to be unemployed as adults. Globally, the rate in 2009 was only slightly higher, at 2.7. These numbers suggest youth unemployment is a prevalent and growing problem in the modern economies worldwide.

2.2 – Determinants of Youth Unemployment

A substantial amount of literature on youth unemployment aims to identify the various factors that determine whether young people are unemployed. Scarpetta et al. (2010) point to disadvantages for young individuals without higher education qualifications. In an all-encompassing assessment, Freeman and Wise (1982) find a number of key determinants including overall labor market booms and busts, the youth proportion of the total population, and the minimum wage. The authors also find young people coming from poor families are less likely to be employed than those from wealthy upbringings, and that race is a determinant of youth unemployment to the extent that black youths are more frequently unemployed than whites. Finally, Freeman and Wise cite the relationship between youth unemployment and the

[2] For its definition of "youth," the report considers individuals aged 15 to 24.

behavior of individuals during high school, in particular regarding academic performance and employment history.

Of the determinants they catalog, Freeman and Wise find the most important is the overall economy, and in particular whether it is in a recession or an expansion. Additional studies make conclusions in support of this finding. Bell and Blanchflower (2011) report that recessionary job losses are most likely to occur in the young age cohorts of 15 to 24 and 25 to 34. Verick studies the recent economic crisis in particular and finds it has made young people more vulnerable to unemployment, with magnitudes varying by country (Verick 2009). For a panel of more than 70 countries around the world, Choudry, Marelli, and Signorelli (2012) uncover evidence that financial crises have positive and significant effects on youth unemployment rates. The authors go on to compare the effects for young people and those for the overall population, observing that adverse recessionary employment effects are larger among youths relative to adults. Looking specifically at students who graduate college in the midst of recessions, Kahn (2008) finds they experience decreased job acquisition and depressed wages. These phenomena occur despite slightly higher educational attainment among recession-era graduating cohorts. On a related note, Clark (2011) investigates whether recessions result in increased enrollment in post-secondary schooling by weakening youth labor markets. Among young people in England, the study finds strong positive effects for youth unemployment on enrollment for both males and females.

2.3 – Measures of Unemployment

Labor economics literature studying unemployment generally focuses on two particular measures: the unemployment rate and unemployment duration. A number of publications (Chiswick et al. 1997; Blanchard and Katz 1996; Bianchi and Zoega 1998) base their analysis on only the rates of unemployment. However, as Gradin, et al. (2012) indicate, it is not sufficient to simply gauge the incidence of unemployment via unemployment rates. Rather, the authors argue research must also address the length of spells for individuals experiencing unemployment. They contend long term unemployment is more detrimental to individual well-being, in addition to being more damaging for long term employment prospects. These arguments are further supported by analysis from Layard et al. (1991), indicating in many countries, variation in unemployment is driven by variation of average unemployment spell length. Existing studies report a number of key determinants for this individual-level unemployment duration. Unemployment insurance benefits and the share of young workers in the labor force are two such determinants (Valletta and Kuang 2012). Arulampalam and Stewart (1995) examine unemployment duration in Britain between 1978 and 1987, and find significant effects for income and local unemployment rates. Evidence for the impact of unemployment benefits on spell length has also been found (Caliendo, Tatsiramos, and Uhlendorff 2013). Finally, and as anticipated, Gradin, Canto, and del Rio (2012) explore the link between the recent global recession and unemployment spell lengths in certain EU countries. They find that the economic slowdown increased durations in Spain, Portugal, Greece, the UK, France, Italy, and Poland.

3 – Model and Methods of Analysis

3.1 – Introduction to Event History Analysis

To the extent that events and the timing of their occurrence are relevant to social scientists, event history analysis is a useful tool for researchers in the discipline. Event history analysis is conducted on observations with associated longitudinal data. There are a variety of event history models, and certain aspects of event history analysis are consistent across them. For one, the analyses can be boiled down to the transition between one state and another. Consequently, dependent variables in event history analysis measure how long an observation spends in an initial state before an "event" occurs, moving the observation to a different state. Duration is expressed as a continuous, positive random variable T, and states can be denoted in a variety of ways (e.g. s_1, s_2). Event history analysis originated from the field of biostatistics. For this reason, the analyses have historically made use of the terms "survival" and "failure". This remains true in social science applications (Box-Steffensmeier and Jones 2004, chap. 4). Another important aspect of event history models is that they allow for analysis in the presence of observations that are censored. Censoring occurs when a particular observation cannot be observed to experience an event. This does not mean the observation does not experience the event, but rather in the time frame of the study, the transition between states is not observed. To summarize, in event history analysis, a subject "survives" in an initial state and is subject to "risk of failure" until the failure (event) occurs, or until the observation is censored. Generally, event history analysis is concerned with modeling hazard rates, which represent the risk of a failure occurring at a specific time given that the subject has not experienced a failure prior to that time. Specifics on the calculation of hazard rates are explored in the sections that follow.

There are a host of examples in the literature of longitudinal analysis applied to unemployment duration. Meyer (1990) and Moffitt (1985) both use non-parametric hazard modeling techniques to explore the effect of unemployment insurance on unemployment spell lengths. This method is also applied in a study of the determinants of unemployment in Russia (Foley 1997). Additionally, Chuang (1999) studies unemployment duration among Taiwanese university graduates using a parametric approach (Weibull distribution).

3.2 – Kaplan-Meier Estimation

In the analysis that follows, the distribution of unemployment duration periods is obtained via Kaplan-Meier estimators (Kaplan and Meier 1958). The Kaplan-Meier estimator is a nonparametric maximum likelihood estimator which involves calculating a hazard rate in each time period for the population at risk of experiencing an event. Within the context of our analysis, the at risk population is comprised of individuals who are at risk of becoming employed.[3] We provide a more detailed description of the factors affecting risk in section 2.3.2. In Kaplan-Meier estimation the hazard is calculated separately at each point, meaning the result is a discrete distribution (Moffitt 1985).

For a population of size n, one can observe k distinct event times $t_1 < t_2 < \cdots < t_k$. Each event t_i is related to an n_i, the number of individuals that are at risk at said time, and d_i, the number of deaths at t_i. Individuals that are marked at risk at time t_i have either not yet experienced the event or have failed specifically at time t_i.

[3] It is worth noting that employment is one of a number of possible exit events. Others could be dropping out of the labor force, going back to school full time, or dying.

The probability that an individual will have a lifetime that exceeds time t, $S(t)$, is calculated by multiplying a sequence of conditional survival probability estimators from those at risk and actual deaths:

$$\hat{S}(t) = \prod_{t_i \leq t} \frac{n_i - d_i}{n_i}. \tag{1}$$

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Thus, the Kaplan-Meier curves present a preliminary univariate analysis to better understand when different groups of individuals survive or fail in the system. In our case, it allows for observation of the proportion of young, educated individuals who survive (in our context continue to be unemployed) or fail (become employed).

3.3 – Cox Proportional Hazards Regression

A more nuanced analysis of unemployment spells arises from modeling the hazard rate in terms of additional variables. The goal is to determine if these covariates have an impact on unemployment duration. To avoid erroneous model specification, and for ease of interpretation of results, we opt for a nonparametric approach to this branch of our analysis. In particular, we adopt the most common nonparametric specification, namely the Cox proportional hazards model ("Cox model" hereafter). The Cox model is a seminal statistical framework that was introduced by Sir David Cox in 1972, and has been used widely since its inception (Box-Steffensmeier and Jones 2004, chap. 4).

The Cox model is applicable to data with information for individuals not only on failure times but also, crucially, additional relevant covariates. The model allows for analyzing if, and how, these additional covariates impact the distribution of failures over time (Cox 1972). The Cox model is a proportional hazards model whereby the effect of a covariate amounts to a multiplication of the baseline hazard. In accordance with Cox's model, for the jth individual the hazard rate can be written as

$$h_j(t) = h_0(t)\exp(\boldsymbol{\beta}'\boldsymbol{z_j}), \tag{2}$$

where $\boldsymbol{\beta}$ is the $(p \times 1)$ vector of regression parameters, $\boldsymbol{z_j}$ is the $(1 \times p)$ vector of covariates for individual j, and $h_0(t)$ is the (unknown) function for the baseline hazard. Cox estimates are generated via a partial likelihood estimation process. Based on equation (2), the partial likelihood function can be written as

$$\mathcal{L}(\beta) = \prod_{i:C_i=1} \left[\frac{\exp(\boldsymbol{\beta}' \boldsymbol{z_i})}{\sum_{j:Y_j \geq Y_i} \exp(\boldsymbol{\beta}' \boldsymbol{z_j})} \right]^{\delta_i}, \quad (3)$$

where the definition of δ_i is 0 in the case of a censored observation and 1 with an uncensored observation. Finally, via log-transformation of (3), one can obtain a log-likelihood function. Then, estimates of the β terms can be generated by maximizing this log-likelihood.

If parameter estimates are exponentiated, they are interpreted as hazard ratios (Box-Steffensmeier and Jones 2004, chap. 4). In this case, hazard ratios less than one correspond to a negative correlation between the hazard and the covariate.

With failure-time data enumerated by a discrete time variable, it is possible for events to occur at the same time, or "tie". In fitting a Cox model, adjustments must be made in light of this possibility. The partial likelihood function cannot account for ties inherently. As a result, the partial likelihood must be approximated. A number of methods exist to perform this approximation, and we opt for the Breslow approach due to its straightforward nature.[4]

The goal of our own application of the Cox model is to assess not only the effects of given covariates on unemployment duration, but also the differences that spatial flexibility (before and after the recession) elicits in these effects. To do so, we include spatial flexibility and timing relative to the recession as dummy variables and allow for interaction effects.[5] This allows me to parse out an added level of detail that is critical in our analysis. For example, if marital status is one of our chosen covariates, we could answer the query, "what is the effect of marital status on unemployment duration for individuals who are spatially flexible before the recession?"

[4] For additional details on the Breslow method of handling ties, see Breslow (1974) and Box-Steffensmeier and Jones (2004, chap. 4).
[5] For more on our variables and their definitions, see Table 2 (Section 2.4.1).

4 – Data

4.1 – Dataset

I use data from the annual March supplement of the Current Population Survey (CPS) to examine individuals' labor market outcomes. The CPS is a household survey administered jointly by the U.S. Census Bureau and the Bureau of Labor Statistics. It incorporates two dimensions: a monthly survey that asks basic labor force and demographic questions, and the March Annual Demographic File and Income Supplement (March CPS) which is generated using a more detailed questionnaire. We access the data from IPUMS CPS, which integrates years of March CPS data into an overall dataset.

Table 1. sample selection criteria

category	criterion
education	bachelor's degree
age	22 to 30 years old
time period	from the years 2003, 2004, 2005, 2006, 2007, 2008, 2010, 2011, 2012, 2013
labor force status	in the labor force
unemployment	experienced at least one week of unemployment in the past calendar year
armed forces status	not an active member of the armed forces

Table 1 presents the selection criteria for our sample of individual-level observations from IPUMS CPS. Foremost, we base the analysis on individuals whose highest educational attainment is a bachelor's degree. In the interest of better addressing the early labor market experiences of college graduates, we exclude advanced degree (master's, Ph.D., and professional degrees) holders from the analysis. Toward the same end, we limit the sample to individuals aged 22 to 30. Using the most recent data, and to relate the analysis to the recent global recession, we examine observations from the years 2003 to 2008 and 2010 to 2013. Only individuals reporting themselves to be "in the labor force" at the time of the survey are considered. The goal being to analyze individuals' diverse experiences regarding unemployment spell length, we examine only those individuals who report at least one week of unemployment in the past year. Finally, we adhere to the custom of excluding active members of the armed forces when dealing with labor market issues. Our data consist of unemployment duration characteristics and relevant socioeconomic covariates as reported by individuals in each year's

March CPS. This means the dataset is built from yearly cross sections of individuals that are randomly sampled from the overall U.S. population. In other words, it is a pooled cross-sectional dataset.

Table 2. variables and their definitions

variable	definition
dependent variable	
unempdur	= duration (in weeks) of unemployment spell for respondent, or length of unemployment for currently unemployed respondents
key independent variables	
flexible	= 1 if respondent has made an intercounty move in the past calendar year for job-related reasons
after	= 1 if the observation is later than the year 2009
personal characteristics	
age	= age of respondent
female	= 1 if respondent is female
married	= 1 if respondent is married
children	= 1 if respondent lives with his/her own children
white	= 1 if respondent is white
immigrant	= 1 if respondent was born outside the United States
hispanic	= 1 if respondent reported Hispanic origin
childhh	= 1 if respondent reports being the child of the household head
locational characteristics	
metro	= 1 if respondent lives in a metropolitan area
origcoast	= 1 if respondent has moved to a different state in the past year, and if the state of origin is California, Connecticut, Washington D.C., Florida, Illinois, Maryland, Massachusetts, New Jersey, New York, North Carolina, Oregon, Pennsylvania, Rhode Island, Texas, Virginia, or Washington
destcoast	= 1 if respondent has moved to a different state in the past year, and if the current state of residence is California, Connecticut, Washington D.C., Florida, Illinois, Maryland, Massachusetts, New Jersey, New York, North Carolina, Oregon, Pennsylvania, Rhode Island, Texas, Virginia, or Washington

Table 2 is a comprehensive list of the variables of choice and their definitions. The variable of interest is “unempdur”, which appears first in the table. This variable is a measure of the lengths of unemployment spells for individual survey respondents. It is constructed using two variables from IPUMS CPS, namely “WKSUNEM1” which measures the number of weeks an individual spent unemployed in the past year and “DURUNEMP” which measures the number of consecutive weeks of unemployment for individuals unemployed at the time of the survey. More specifically, observations representing individuals who are currently employed are coded into “unempdur” as the number of weeks the individual was unemployed in the past year. On the other hand, observations reporting currently unemployed individuals are coded into the variable as the number of weeks they have been unemployed consecutively.[6] In explicit terms, this variable gives a measure (in weeks) of the duration of individuals' unemployment spells over the course of the past year.

The distinction between spatially flexible and inflexible individuals is paramount in our analysis. Hence, it requires explicit coding at the individual level, as does the grouping of observations both before and after the economic crisis. Toward that end we designate two key independent variables of analysis, which are described in Table 2. First is "flexible", which identifies whether an individual exhibits spatial flexibility. Migration literature customarily designates individuals who migrate as "movers" and those who do not migrate as "stayers". Adapting this practice to the context of spatial flexibility, we denote individuals who have moved for job reasons as "flexible" and individuals who have not as "inflexible". For the purposes of our analysis, we consider an individual to be flexible if s/he has moved to a different county for job-related reasons. In designating so called job-related reasons, we make use of the IPUMS CPS variable "WHYMOVE", which identifies a respondent's single main reason for moving. Specifically, we limit job-related reasons to the following survey responses: "New job or job transfer"; and "To look for work or lost job". The second key independent variable shown in table 2 is "after", which denotes whether an observation is from before (= 0) or after (= 1) the crux of the recent global recession. We use 2009 as the reference year. The justification for this revolves around the timing of recessionary increases in both the unemployment rate and the long-term (27+ weeks) unemployment share. From Rothstein (2012) Figure 1, the brunt of these increases took place in 2009. Thus, for our analysis observations from 2003 to 2008 are considered pre-recession, and observations from 2010 to 2013 are considered post-recession. Data from the year 2009 are not used, due to their volatile nature. Sensitivity analysis around choosing 2009 as the reference year reveals its robustness regarding the qualitative nature of our results.

Aside from the key independent variables, our model makes use of a number of personal and locational characteristics available for individuals recorded in the survey. Personal covariates include respondents' ages, as well as marital status, gender, whether respondents live with their own children, race, immigrant status, Hispanic origin, and whether the respondent is the child of

[6] These observations are eventually censored in the analysis, by way of a process described below.

the head of their household. Regarding individuals' locational characteristics, we include covariates measuring residence in metro areas and in U.S. regions. Metro status is determined based on U.S. Census Bureau definitions of metropolitan areas. Finally, we have variables that stratify movers based on their regions of origin and/or destination. The variable "origcoast" is used to denote individuals who have moved in the past calendar year, and who originally lived in areas of relatively high economic activity. For the United States, economic activity is concentrated in the east and west coasts, as well as a select few interior areas. At the state level, we designate California, Connecticut, Washington D.C., Florida, Illinois, Maryland, Massachusetts, New Jersey, New York, North Carolina, Oregon, Pennsylvania, Rhode Island, Texas, Virginia, and Washington as regions of relatively high economic activity. Hence, "origcoast" identifies individuals who move away from one of these regions. By the same token, "destcoast" identifies individuals who move into one of the same states.

Existing literature provides a basis for the inclusion of a number of the selected covariates. In studying unemployment duration in Turkey, Tansel and Tasci (2004) find women to have substantially longer spell durations than men. They also report marital status to have significant effects on unemployment duration for both men and women, although the effect of being married is negative for women and positive for men. The authors' evidence for the effect of age suggests older individuals have relatively lower hazard rates for exiting unemployment. Interestingly, the study also reveals discrepancies in exit rates for both men and women under different definitions of unemployment. Unemployment studies have previously argued an individual's relationship to the household head can significantly impact labor market outcomes. Namely, non-household heads face a more constrained market and greater unemployment (Green and Hendershott 2001). Nickell (1979) reports, among married men in particular, a positive correlation between the expected length of unemployment spells and the number of children. Examination of rural-urban differences in unemployment duration points to increased durations in urban areas (Tansel and Tasci 2004). Finally, in a seminal study of unemployment duration, Katz and Meyer (1990) recognize the impact of geographic characteristics and control for them (in their case using state fixed effects).

Table 3. summary statistics§

group	flexible before		inflexible before		flexible after		inflexible after	
statistic	mean	std. dev.	mean	std. dev.	mean	std. dev.	mean	std. dev.
dependent variable								
unempdur	13.19678	11.49028	14.60561	12.54927	16.30236	12.86090	19.23690	15.34001
key independent variables								
flexible	1.00000	0.00000	0.00000	0.00000	1.00000	0.00000	0.00000	0.00000
after	0.00000	0.00000	0.00000	0.00000	1.00000	0.00000	1.00000	0.00000
personal characteristics								
age	25.26681	2.48128	25.77861	2.46127	25.28183	2.53736	25.72221	2.42868
female	0.49036	0.50123	0.52867	0.49930	0.50300	0.50158	0.48669	0.49994
married	0.24494	0.43119	0.24201	0.42840	0.31128	0.46449	0.20562	0.40425
children	0.05474	0.22807	0.12463	0.33038	0.11908	0.32492	0.12576	0.33165
white	0.85302	0.35502	0.77851	0.41535	0.87648	0.33008	0.77067	0.42050
immigrant	0.08246	0.27579	0.14482	0.35200	0.05364	0.22603	0.11705	0.32155
hispanic	0.07441	0.26313	0.08514	0.27915	0.09252	0.29068	0.09942	0.29929
childhh	0.10953	0.31313	0.29373	0.45558	0.05180	0.22232	0.35454	0.47848
locational characteristics								
metro	0.87731	0.32895	0.90330	0.29562	0.89889	0.30244	0.91933	0.27239
origcoast	0.61139	0.48872	0.17601	0.38092	0.56964	0.49670	0.16072	0.36736
destcoast	0.66168	0.47439	0.08153	0.27371	0.52265	0.50107	0.06833	0.25236
observations	190		2,087		158		2,183	
estimated weighted observations	337,914		3,677,706		295,381		4,121,783	

notes: § values reported are mean and standard deviation estimates based on IPUMS CPS data, calculated with probability weights via the "WTSUPP" variable, using Stata12.

Table 3 gives summary statistics for the variables appearing in the analysis grouped by both spatial flexibility status and timing relative to the recession. The figures presented are based on the CPS sample used throughout our analysis. Probability weights are employed to make the statistics representative of the overall U.S. population. Hence, the mean and standard deviation figures are estimates, calculated using statistical software. The calculations are based on actual observations from a CPS sample, which are subjected to probability weighting in order to be made representative of the United States population at large. This means the calculations are performed on an estimated 0.34 million spatially flexible persons before the recession, 3.68 million inflexible persons before the recession, 0.30 million flexible persons after the recession, and 4.12 million inflexible persons after the recession.

Comparing results across the four groupings, mean values for "unempdur" range from roughly 13 weeks to more than 19 weeks. On average, unemployment spells last longer for individuals who are spatially inflexible. The same can be said for individuals in the post-recession period, compared to the years beforehand. Standard deviation estimators increase after the financial crisis, and are also larger for spatially inflexible individuals. This measure indicates unemployment spell lengths are more volatile among people who lack spatial flexibility, suggesting increased labor market stability among individuals exercising spatial flexibility.

In the interest of clarity, Table 3 reports estimates for the key independent variables, flexible and after. These dummy variables are used to separate the groupings, and have the expected results for mean and standard deviation. Following the key independent variables are personal and locational characteristics.

Mean ages of individuals range from 25 to 26 years old across all four groupings, with relatively similar standard deviation estimates. Before the recession, spatially inflexible individuals are more likely to be female on average, whereas after the recession, the reverse is true. Prior to the recession, the average proportion of spatially flexible individuals who are married is nearly equivalent to that of spatially inflexible individuals. In contrast, post-recession spatially flexible individuals are substantially more likely to be married than their inflexible counterparts. Generally, a higher proportion of spatially inflexible people live with their own children. This is especially true before the recession. An implication is that after the recession job reasons incentivized more families to move who may have previously been "settled in" to a geographic location for social and/or familial reasons.

Before and after the recession, the proportions of spatially flexible individuals who are white are more than 85 percent, whereas inflexible white persons number closer to 77 percent. Spatially inflexible individuals are more likely to be immigrants on average in both the pre- and post-recession periods, while Hispanic proportions do not change much relative to spatial flexibility. Inflexible persons are substantially more likely to be the children of household heads. This is true before the economic crisis, and also to a greater extent after the crisis. This suggests economic benefits of living in the household of one's parents exist, and have added influence in poorer economic times.

Finally, Table 3 reports estimates of the locational characteristics of the population. Of individuals exhibiting spatial flexibility before the economic crisis, nearly 88 percent live in metropolitan areas at the time of analysis. This compares to around 90 percent of inflexible people pre-crisis. In general, a slightly greater proportion of individuals live in metro areas after the crisis. This amounts to roughly 90 percent of the spatially flexible and 92 percent of the inflexible. Among flexible individuals, a majority of the migration taking place revolves around the most economically active regions of the United States. Before 2009, 61 percent of flexible individuals are moving out of the economically active states, while 66 percent of flexible individuals move into them. The variables “origcoast” and “destcoast” also capture the migration behavior of people who move, but are not spatially flexible, i.e. individuals who move for “non-job reasons”. Among the spatially inflexible before 2009, 18 (8) percent of individuals move out of (into) the coasts or other economically active regions. After the economic crisis, 57 and 52 percent of flexible individuals are found to be moving *out of* and *into* these regions, respectively. Among inflexible U.S. residents after the crisis, 16 percent move out of economically high-performing states, while 7 percent move into them.

4.2 – Data Issues

Due to the less-than-perfect nature of the data, issues abound when using the Current Population Survey to measure unemployment duration. Sider (1985) expounds on the myriad of issues with CPS unemployment data. Many of the problems the author raises are related to survey and questionnaire design, meaning their relevance persists to this day. Response bias is one issue of particular importance. Sider’s paper argues unemployment stints that are in progress tend to spike at round numbers. The data that are reported in the CPS refer to consecutive weeks since a currently employed individual became unemployed. However, the data cluster disproportionately at “round” durations such as monthly and quarterly. In other words, unemployment stints totaling 4 weeks (roughly one month) are more likely to occur in the dataset than unemployment stints totaling 3 or 5 weeks. But Sider goes on to explain these reporting errors appear to have a tendency to offset. This tendency helps to mitigate errors (Sider 1985).

Owing to the fact that the Current Population Survey is derived from person-to-person interviews, its data is subject to issues associated with self-reporting. Individuals are asked to report on their own employment status and the length of their own unemployment spell. However, the official definition of "unemployed" is something that may not be known to survey respondents. This is primarily due to the ambiguity between being unemployed (but in the labor force) and being a non-participant in the labor force. One argument is that individuals will ignore periods where they officially drop out of the labor force, as well as periods of intermittent employment, and instead report an unemployment duration dating back to their initial job loss (Rothstein 2011).

Additionally, a number of more generalized issues are inherent in Current Population Survey data. Poterba and Summers (1984) describe problems with recording and coding of survey responses, as well as with the logical consistency of what the respondents themselves report in CPS interviews. The authors conduct their analysis by comparing initial interview results with reconciled results from a follow-up interview administered to a subsample of CPS households. In their measurement of coding errors, the authors report more than ten percent of individuals who are determined to be genuinely unemployed are incorrectly classified as not in the labor force initially (Poterba and Summers 1984).

On the topic of logical consistency, Poterba and Summers (1984) explore whether individuals who responded to successive CPS surveys gave answers that were in accordance logically from month-to-month. The study looks specifically at individuals who are unemployed in two consecutive months. By differencing the reported duration of unemployment from one month to the next, it finds that more than two-thirds of these individuals gave survey responses that were logically inconsistent. Evidence also suggests this inconsistency was more pronounced with people experiencing longer stints of unemployment. However, the authors conclude their study by indicating that, while these errors exist in the Current Population Survey, the interviewing and coding methods specific to the CPS are likely to ensure that they occur less frequently than in other datasets. The overarching takeaway from the paper is not that CPS data should no longer be used. Instead, the argument is the errors investigated may introduce bias in CPS data, and this potential bias should be addressed (Poterba and Summers 1984).

The aforementioned Current Population Survey issues have prompted a number of unemployment duration studies to use other datasets. Moffitt (1985) and Meyer (1990) conduct analysis using Continuous Wage and Benefit History (CWBH) data. CWBH data are derived from the administrative records of the United States Unemployment Insurance program. The dataset has accurate information on the number of weeks individuals have collected benefits, and how many additional weeks of benefits individuals are able to collect, as well as the levels of benefits themselves. However, these data also are not without their limitations. For one, only males are observed. But the truncation of CWBH data is arguably a more substantial caveat. The data do not extend beyond the point where Unemployment Insurance benefits are exhausted for a given individual (Moffitt 1985).

Despite the issues inherent in the Current Population Survey, the dataset has particular aspects that make it ideal for the analysis that follows. Many of these positive elements are described in detail by Rothstein (2011). Foremost among these is the CPS's characteristically large sample sizes. In addition to size, the data also have the advantage of being current. Unlike the CWBH, the CPS allows for examination of individuals not receiving unemployment benefits during the period of time being studied. Finally, the CPS allows for a more detailed analysis of why unemployment stints end, in particular by distinguishing between individuals who exit the labor force and those who get jobs. Self-reporting issues remain a concern, although they may have been mitigated to some extent by a redesign of CPS procedures in 1994 (Rothstein 2011).

5 – Analysis and Results

5.1 – Kaplan-Meier Estimation

As a first step in the analysis, we obtain Kaplan-Meier curves for specific groups of individuals within the sample. We then employ a "Cox" test[7] to assess differences in the Kaplan-Meier survival curves across the groups being studied. In practical terms, the Cox test amounts to

[7] We use the term *Cox test* as defined in StataCorp L.P. (2013).

fitting a Cox proportional hazards regression and performing a Wald test on the results (StataCorp L.P. 2013).

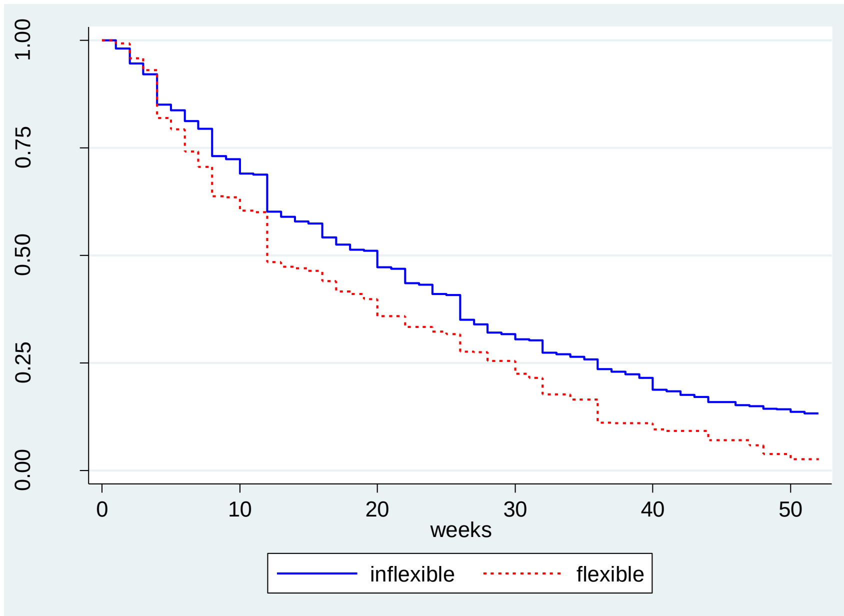

Figure 1. Kaplan-Meier survival curves – inflexible vs flexible, 2003-2008 & 2010-2013

Table 4. Cox test for equality of survival curves – inflexible vs flexible, 2003-2008 & 2010-2013

flexibility	events observed	events expected	relative hazard
inflexible	5027864.19	5142387.83	0.9806
flexible	474001.53	359477.91	1.3234
total	5501865.72	5501865.72	1.0000
Wald χ^2 (1 d.f.)	16.90***		

***, **, and * refer to significance at the 0.01, 0.05, and 0.1 levels, respectively.

Figure 1 takes the entire weighted sample in all years studied (roughly 8.43 million individuals) and plots the Kaplan-Meier survival functions for the spatially inflexible versus the spatially flexible. The blue (solid) line represents the inflexible, and the red (dashed) line the flexible. As the figure refers to those experiencing unemployment, survival refers to remaining unemployed, meaning the y-axis represents the percent of individuals still unemployed. The x-axis plots weeks, i.e. the duration of unemployment spells. Vertical and horizontal gaps between the curves plotted indicate differences among the groups in question.[8] By revealing vertical and horizontal gaps between the curves, Figure 1 appears to indicate shorter unemployment durations among flexible individuals. To more explicitly describe this phenomenon, one can refer to median survival times, where $S(t) = 0.5$. The median survival time (i.e. unemployment spell length) for inflexible people is 20 weeks. This is compared to 12 weeks for flexible individuals, a substantially lower figure. Additionally, we estimate average unemployment duration for the two groupings, taking into account weighting and censored observations. For inflexible individuals the average is 17.05, compared to 14.65 for flexible people. These statistics suggest spatial flexibility improves labor market outcomes by decreasing the duration of unemployment at the individual level. Table 4 reaffirms this implication. It reports the result of a Cox test between inflexible and flexible persons, suggesting the survival function of unemployment duration for the flexible is significantly different from the survival function of unemployment duration for the inflexible.

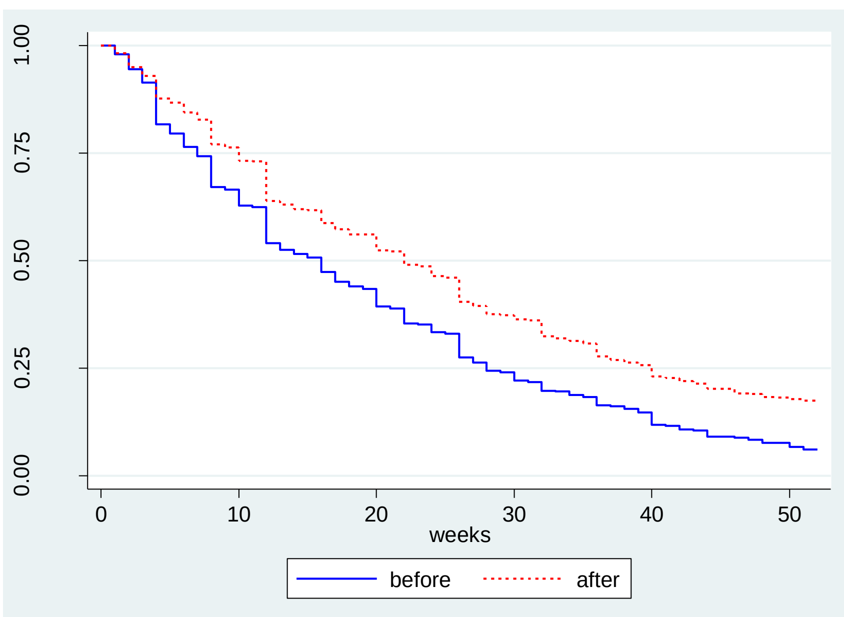

Figure 2. Kaplan-Meier survival curves – before vs after 2009

[8] An interpretation of vertical gaps is that at a given point in time, one group has a greater percentage still surviving. Horizontal gaps can be interpreted to mean that it takes one group more time to experience a given number of failures.

Table 5. Cox test for equality of survival curves – before vs after 2009

timing	events observed	events expected	relative hazard
before	2740875.46	2245056.54	1.2450
after	2760990.26	3256809.20	0.8598
total	5501865.72	5501865.72	1.0000
Wald χ^2 (1 d.f.)	77.99***		

***, **, and * refer to significance at the 0.01, 0.05, and 0.1 levels, respectively.

I hypothesize that the recent recession impacted individuals' unemployment durations, regardless of spatial flexibility. To better characterize this impact, we compare Kaplan- Meier survival curves for all individuals (both flexible and inflexible) before and after 2009. The results are reported in Figure 2. As in Figure 1, the y- and x-axes measure the percent of individuals surviving (staying unemployed) and the time elapsed in weeks. Observations from before 2009 are represented by the solid blue line, while those after 2009 are represented by the dashed red line. The gaps that exist between the curves suggest post-recession individuals experience longer unemployment durations than their pre-recession counterparts. Estimated statistics (accounting for censoring) on the survival times of both groupings provide further evidence of the group-wise differences. For one, median survival time before the recession is 16 weeks, while median survival time afterward is 22 weeks. A similar discrepancy exists between average survival times, with the pre-recession average estimated to be 14.49 weeks and the post-recession estimate at 19.04 weeks. As before, these averages account for probability weights and censoring. The Cox test results reported in Table 5 confirm that statistically significant differences exist between subjects before and after 2009.

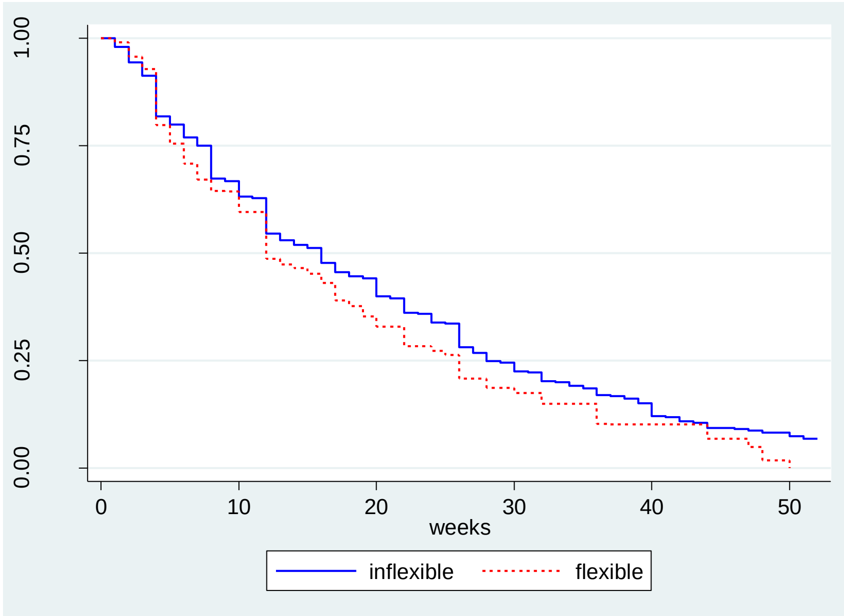

Figure 3. Kaplan-Meier survival curves before 2009 – inflexible vs flexible

Table 6. Cox test for equality of survival curves before 2009 – inflexible vs flexible

flexibility (before)	events observed	events expected	relative hazard
inflexible	2493563.80	2531785.98	0.9861
flexible	247311.66	209089.48	1.1845
total	2740875.46	2740875.46	1.0000
Wald χ^2 (1 d.f.)	3.46*		

***, **, and * refer to significance at the 0.01, 0.05, and 0.1 levels, respectively.

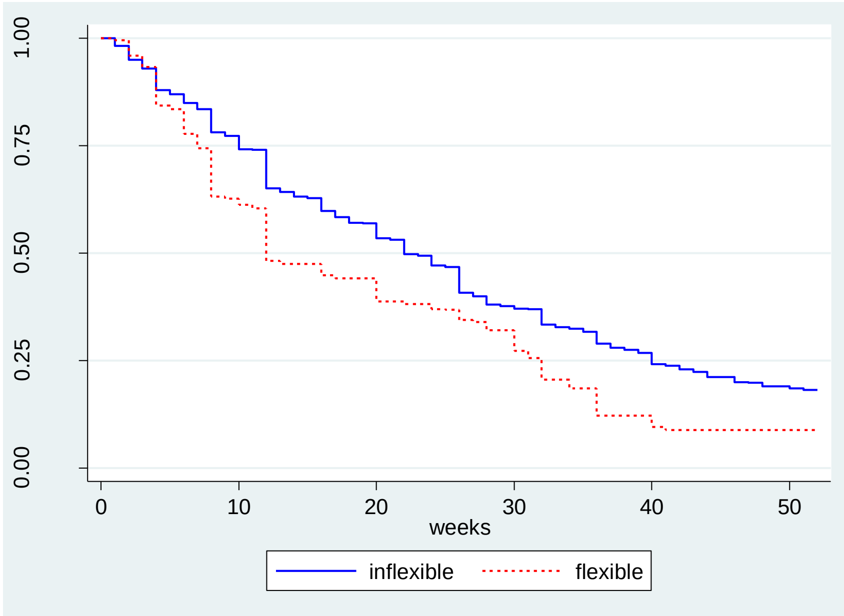

Figure 4. Kaplan-Meier survival curves after 2009 – inflexible vs flexible

Table 7. Cox test for equality of survival curves after 2009 – inflexible vs flexible

flexibility (after)	events observed	events expected	relative hazard
inflexible	2534300.39	2602335.38	0.9781
flexible	226689.87	158654.90	1.4368
total	2760990.26	2760990.26	1.0000
Wald χ^2 (1 d.f.)	12.41***		

***, **, and * refer to significance at the 0.01, 0.05, and 0.1 levels, respectively.

Taking into account only subjects from before 2009, Figure 3 plots survival curves for spatially inflexible versus spatially flexible individuals. On the other hand, Figure 4 plots spatially inflexible versus spatially flexible people after 2009. The graphs suggest more favorable unemployment durations among the spatially flexible. This finding is further evidenced by estimates median and mean duration values for each grouping (which we calculate using methods that account for censored observations). Before 2009, median survival time is 16 weeks for inflexible people and 12 weeks for flexible people. After 2009, inflexible people survive 22 weeks at the median and flexible people survive 12 weeks at the median. In other words, a gap indicating shorter median unemployment durations among the spatially flexible exists in both figures, but this gap is more pronounced in Figure 4 (post-2009). Additionally, a Cox test (Table 6) reports statistical significance at the 0.1 level for the pre-2009 comparison of flexible versus inflexible people. But, a greater level of significance, 0.01, is reported for the post-2009 comparison (Table 7). This suggests the impact of spatial flexibility on unemployment duration is more robust after the economic crisis.

Table 8. Median and Average Survival Times

duration	flexible before	inflexible before	flexible after	inflexible after
median	12	16	12	22
average	13.197	14.606	16.302	19.237

Table 8 synthesizes the results of the survival curve analysis, presenting estimates of median and average unemployment durations among the four groupings defined by flexibility and timing relative to the recession. As previously discussed, the spatially flexible have lower median and average unemployment durations relative to the inflexible. This is true both before and after the recession.

5.2 – Cox Model Estimation

In the next step of our analysis, we fit a Cox model with "unempdur" as the dependent variable, and a number of covariates surmised to impact the duration of unemployment. To adhere to the process described in the final paragraph of Section 2.3.3, we make use of interactions between each of these covariates and specified values of the key independent variables "spatial" and "after". Hence, for several specifications of the Cox model we obtain parameter estimates, and report robust standard errors. The results tables that follow report the coefficients from the fitted Cox regression, which can be translated into hazards by exponentiation.

Table 9. Cox Proportional Hazard Model estimates before the recession§

variable	(1) flexible = 1	(2) flexible = 0	(3) difference = (1) - (2)
flexible			-0.398
			(1.300)
age	-0.015	-0.057***	0.041
	(0.045)	(0.014)	(0.047)
female	-0.416**	0.250***	-0.666***
	(0.194)	(0.063)	(0.204)
married	-0.152	0.134	-0.285
	(0.286)	(0.090)	(0.300)
children	-0.194	-0.075	-0.118
	(0.321)	(0.101)	(0.336)
white	0.143	0.260***	-0.117
	(0.280)	(0.088)	(0.293)
immigrant	-0.122	-0.324***	0.202
	(0.361)	(0.109)	(0.377)
hispanic	-0.692	0.096	-0.788*
	(0.449)	(0.103)	(0.460)
childhh	-0.656**	-0.364***	-0.292
	(0.283)	(0.078)	(0.294)
metro	0.089	0.009	0.081
	(0.306)	(0.089)	(0.319)
origcoast	-0.162	0.073	-0.235
	(0.232)	(0.097)	(0.252)
destcoast	0.030	0.094	-0.064
	(0.248)	(0.125)	(0.278)
observations	2,277		
no. of subjects‡	4,015,620		
% censored‡	31.7%		
χ^2 (27 d.f.)	129.60***		

notes: § robust standard errors in parentheses. ‡ probability weighted based on the IPUMS CPS variable "wtsupp". ***, **, and * refer to significance at the 0.01, 0.05, and 0.1 levels, respectively.

Table 9 presents estimation results from Cox model specifications comparing individuals from before the recession on the basis of spatial flexibility. Column (1) reports parameter estimates for the model specified for flexible individuals (where the variable flexible is assigned a value of 1). Estimates on the interaction terms in this model specification are the differences in covariate effects between movers and stayers, and are reported in column (3). Finally, column (2) provides results for the model specified for inflexible individuals (flexible = 0). The overall statistical significance of the model is high, as a Wald chi-square test returns significance at the 1 percent level. The number of observations before the economic crisis is 2,277, a number which is probability weighted to represent more than 4 million subjects for the analysis. The percentage of observations censored is 31.7.

In the previously discussed Kaplan-Meier survival curve analysis, we found general significance in the effects of spatial flexibility and the recent recession on the length of unemployment spells.

With the Cox model results in Table 9 we hope to explore whether additional covariates change the impact of these events. For flexible individuals (column (1)), the results suggest that, generally, an individual's personal characteristics generally do not bring about any change in the impact of flexibility itself. Many of the estimates for these individuals are not statistically significant. However, the results suggest flexible women fare worse in the search for employment before the recession. The coefficient of the "female" variable is negative and statistically significant, meaning flexible women face substantially lower exit rates of unemployment relative to flexible men. Another variable with a negative coefficient and statistical significance among flexible individuals is "childhh". This indicates that individuals exercising spatial flexibility to move in with their parents also have trouble finding employment relative to other spatially flexible people. Examining inflexible individuals before the economic crisis, Table 9 reveals age, immigrant status, and being the child of the household head have significant negative impacts. In other words, people who do not exercise spatial flexibility are less likely to exit unemployment as they get older, if they are immigrants, and/or if they live with their parents. On the other hand, inflexible women and inflexible people reporting their race to be white alone are subject to higher rates of exiting unemployment relative to other inflexible individuals before 2009. Looking at the difference terms in column (3) of Table 9 allows for parsing out the impact of spatial flexibility on unemployment durations for a given demographic group. The estimate for the difference in the female coefficients is significant and negative. This provides evidence that spatial flexibility is not a benefit for women before 2009. The same can be said (albeit with less statistical significance) for individuals of Hispanic origin.

Table 10. Cox Proportional Hazard Model estimates after the recession§

variable	(1) flexible = 1	(2) flexible = 0	(3) difference = (1) - (2)
flexible			-0.813
			(1.595)
age	-0.011	-0.071***	0.061
	(0.064)	(0.014)	(0.066)
female	-0.331	0.269***	-0.600**
	(0.248)	(0.066)	(0.257)
married	-0.175	0.022	-0.197
	(0.283)	(0.084)	(0.295)
children	-0.155	-0.274***	0.119
	(0.423)	(0.094)	(0.433)
white	0.205	0.381***	-0.176
	(0.262)	(0.076)	(0.273)
immigrant	-0.228	-0.066	-0.162
	(0.383)	(0.092)	(0.393)
hispanic	0.127	-0.214**	0.340
	(0.376)	(0.091)	(0.387)
childhh	-0.744	-0.559***	-0.185
	(0.504)	(0.077)	(0.510)
metro	-0.118	-0.085	-0.032
	(0.309)	(0.111)	(0.329)
origcoast	0.025	0.148	-0.123
	(0.282)	(0.107)	(0.302)
destcoast	-0.111	0.053	-0.164
	(0.295)	(0.143)	(0.328)
observations	2,341		
no. of subjects‡	4,417,163		
% censored‡	37.5%		
χ^2 (27 d.f.)	163.29***		

notes: see Table 9.

Table 10 presents additional Cox estimation results for a specification comparing those who move for job reasons and those who don't after the recession. Coefficients reported in columns (1), (2), and (3) are akin to those reported in the equivalent columns of Table 9. A Wald chi-square test for overall model robustness is significant at the 1 percent level. A total of 2,341 individuals appear in our sample after the economic crisis, giving a probability weighted 4.4 million subjects for the analysis, with 37.5 percent censored.

Estimates reported in Table 10 give an indication of the impacts of personal characteristics on the effect of spatial flexibility after the recession. Coefficients in column (1) reveal that, among flexible people, demographic and locational attributes do not have measurable impacts on spatial unemployment durations one way or another. Estimates in this column are uniformly lacking in statistical significance. This is not the case among inflexible individuals, however. Negative and significant estimates are reported for "age", "children", "hispanic", and "childhh". These indicate that after the recession, inflexible individuals are less likely to exit unemployment as they age, if they have children, if they report Hispanic origins, and/or if they live with their parents. We look to the difference terms for evidence on how flexibility impacts individuals with given characteristics. Similar to their counterparts before the recession, women after the recession appear not to benefit from spatial flexibility. The negative and significant difference estimate indicates that: (a) inflexible women face higher unemployment exit rates relative to other inflexible people; (b) flexible women face lower rates relative to other people exhibiting spatial flexibility; or (c) both.

6 – Conclusion

With regard to the unemployment duration, the evidence indicates benefits (shorter spell lengths) arising from spatial flexibility. Spatially flexible people experience shorter periods of unemployment than the spatially inflexible. As anticipated, the financial crisis also impacts unemployment durations, making them generally longer. But, importantly, the crisis increased the beneficial effects of spatial flexibility in general among the individuals studied. In particular, the impact of spatial flexibility among all individuals is both larger in magnitude and of greater statistical significance after 2009. While the choice of whether or not to move for a job was not trivial before the crisis, its importance only increased as economic conditions worsened.

Additionally, we find the effect of spatial flexibility can vary based on the personal characteristics of individuals. Interestingly, women who are spatially flexible perform worse than other people who are spatially flexible, and women who are inflexible perform better than others who are inflexible. This difference is significant both pre- and post-2009, evidencing the striking result that spatial flexibility does not appear to be a benefit for women either before or after the recession. Looking at inflexible individuals, we find being white to be a benefit both before and after the recession. The opposite is true for being the child of the household head. People living with their parents before the crisis are less adept at exiting unemployment whether or not they are spatially flexible. After the crisis, this remains true among inflexible individuals. It would appear that living with one's parents is a serious detriment to one's employment prospects. Before and after 2009, inflexible people become less likely to find employment as they age. This cannot be said for flexible people, however. For all of the personal characteristics with substantial effects on unemployment durations and the related impacts of spatial flexibility, a number of other attributes were not consequential. No impacts were found for marital status, metropolitan area residence, or regional characteristics (i.e. whether an individual was moving into or out of an economically active area).

Future research endeavors would do well to pursue this issue with more specialized data. We use a sample that allows me to study the early labor market activity of individuals. However, it would be ideal to analyze individuals searching specifically for their first career-type employment. This type of analysis could have stronger implications, to the extent that an individual's first job after graduation is especially crucial to their life-course labor market performance. Additionally, this analysis is limited to individuals with unemployment durations of at most one year. The ability to study those with longer durations is a luxury that could be afforded by a more specialized dataset.

References

Arulampalam, W., & Stewart, M. B. (1995). The determinants of individual unemployment durations in an era of high unemployment. *The Economic Journal,* 321-332.

Avery, C., & Turner, S. (2012). Student Loans: Do College Students Borrow Too Much Or Not Enough?. *The Journal of Economic Perspectives*, 26(1), 165-192.

Bell, N. F., & Blanchflower, D. G. (2011). Youth unemployment in Europe and the United States. *Nordic Economic Policy Review*, *1*, 11-37.

Bianchi, M., & Zoega, G. (1998). Unemployment Persistence: Does the size of the shock matter?. *Journal of Applied Econometrics*, *13*(3), 283-304.

Blanchard, O., & Katz, L. F. (1996). *What we know and do not know about the natural rate of unemployment* (No. w5822). National Bureau of Economic Research.

Bowles, S. (1970). Migration as investment: empirical tests of the human investment approach to geographical mobility. *The Review of Economics and Statistics*, *52*(4), 356-362.

Box-Steffensmeier, J. M., & Jones, B. S. (2004). *Event history modeling: A guide for social scientists*. Cambridge New York: Cambridge University Press.

Breslow, N. (1974). Covariance analysis of censored survival data. *Biometrics*, 89-99.

Caliendo, M., Tatsiramos, K., & Uhlendorff, A. (2013). Benefit Duration, Unemployment Duration And Job Match Quality: A Regression-Discontinuity Approach. *Journal of Applied Econometrics*, *28*(4), 604-627.

Chiswick, B. R., Cohen, Y., & Zach, T. (1997). The labor market status of immigrants: effects of the unemployment rate at arrival and duration of residence. *Industrial and labor relations review*, 289-303.

Choudhry, M. T., Marelli, E., & Signorelli, M. (2012). Youth unemployment rate and impact of financial crises. *International Journal of Manpower*, *33*(1), 76-95.

Chuang, H. L. (1999). Estimating the determinants of the unemployment duration for college graduates in Taiwan. *Applied Economics Letters*, *6*(10), 677-681.

Clark, D. (2011). Do Recessions Keep Students in School? The Impact of Youth Unemployment on Enrolment in Post-compulsory Education in England. *Economica*, *78*(311), 523-545.

Cox, D. R. (1972). Regression models and life-tables. *Journal of the Royal Statistical Society. Series B (Methodological)*, 187-220.

Dooley, D., Fielding, J., & Levi, L. (1996). Health and unemployment. *Annual review of public health*, *17*(1), 449-465.

Foley, M. C. (1997). Determinants of unemployment duration in Russia. Economic Growth Center. *Discussion Paper No. 779.* Yale University, August.

Freeman, R. B., & Wise, D. A. (1982). The Youth Labor Market Problem: Its Nature Causes and Consequences. In *The youth labor market problem: Its nature, causes, and consequences* (pp. 1-16). University of Chicago Press.

Gradin, C., Canto, O., & del Rio, C. (2012). Unemployment and Spell Duration during the Great Recession in the EU. *Documentos de Traballo WP1205, Departamento de Economía Aplicada, Universidade de Vigo*.

Green, R. K., & Hendershott, P. H. (2001). Home-ownership and unemployment in the US. *Urban Studies*, *38*(9), 1509-1520.

International Labor Organization (ILO). (2010). Global employment trends for youth. *Special Issue on the Impact of Global Economic Crisis on Youth,* International Labour Organization, Geneva.

Kahn, L. B. (2010). The long-term labor market consequences of graduating from college in a bad economy. *Labour Economics*, *17*(2), 303-316.

Kaplan, E. L., & Meier, P. (1958). Nonparametric estimation from incomplete observations. *Journal of the American statistical association*, *53*(282), 457-481.

Katz, L. F., & Meyer, B. D. (1990). The impact of the potential duration of unemployment benefits on the duration of unemployment. *Journal of public economics*, *41*(1), 45-72.

Layard, R., Layard, P. R. G., Nickell, S. J., & Jackman, R. (2005).*Unemployment: macroeconomic performance and the labour market*. Oxford University Press.

Miriam King, M., S. Ruggles, J. T. Alexander, S. Flood, K. Genadek, M. B. Schroeder, B. Trampe, & R. Vick. Integrated Public Use Microdata Series, Current Population Survey: Version 3.0. [Machine-readable database]. Minneapolis: University of Minnesota, 2010.

Meyer, B. D. (1990). Unemployment insurance and unemployment spells. *Econometrica,* 58(4), 757-782.

Moffitt, R. (1985). Unemployment insurance and the distribution of unemployment spells. *Journal of Econometrics*, 28, 85-101.

Nickell, S. (1979). Estimating the probability of leaving unemployment.*Econometrica: Journal of the Econometric Society*, 1249-1266.

Poterba, J. M., & Summers, L. H. (1984). Response variation in the CPS: caveats for the unemployment analyst. *Monthly Labor Review,* 107(3), 37-43.

Reed, M., & Cochrane, D. (2012). Student Debt and the Class of 2011. *Project on Student Debt*.

Rothstein, J. 2011. "Unemployment Insurance and Job Search in the Great Recession," *Brookings Papers on Economic Activity, Economic Studies Program, The Brookings Institution,* vol. 43(2 (Fall)), pages 143-213.

Scarpetta, S., Sonnet, A., & Manfredi, T. (2010). Rising youth unemployment during the crisis. *Documents de travail de l'OCDE sur les affaires sociales, l'emploi et les migrations*, (106).

Schachter, J. (2003). *Migration by race and Hispanic origin: 1995 to 2000*. US Department of Commerce, Economics and Statistics Administration, US Census Bureau.

Sider, H. (1985). Unemployment duration and incidence: 1968-82. *The American Economic Review*, 75(3), 461-472.

Sjaastad, L. A. (1962). The costs and returns of human migration. *The journal of political economy*, 80-93.

StataCorp L.P. (2013). *Stata Survival Analysis and Epidemiological Table Reference Manual*. College Station: StataCorp LP.

Tansel, A., & Tasci, H. M. (2004). Determinants of unemployment duration for men and women in Turkey. *Institute for Study of Labor (IZA),* Discussion Paper No: 1258, Bonn: IZA.

Valletta, R., & Kuang, K. (2012). Why is unemployment duration so long. *FRBSF Economic Letters*, *3*.

Van Ham, M., & Hooimeijer, P. (2009). Regional differences in spatial flexibility: long commutes and job related migration intentions in the Netherlands. *Applied spatial analysis and policy*, *2*(2), 129-146.

Verick, Sher. (2009). Who is hit hardest during a financial crisis? The vulnerability of young men and women to unemployment in an economic downturn. *IZA Discussion Papers*, No. 4359, http://nbn-resolving.de/urn:nbn:de:101:1-20091105792