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All Recessions Are Not Equal: The Effect of Sectoral Shifts on Unemployment Using Regional Data

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ABSTRACT

This thesis investigates the effect that variation in employment between industries has had on the depth of recession faced by Metropolitan Statistical Areas (MSAs) in the United States. This analysis is limited to the previous two national recessions. I use regression analysis to find that increases variation in employment has a significant effect on the maximum increase in unemployment rate in MSAs after controlling for relevant MSA characteristics. In this framework I also find that increases in education could mitigate the negative effects of this variation. I include several other measures of depth of recession including the fall in economic conditions and length for real GDP to recover to its pre-recession levels. I find that the measure of variation is significant in explaining falls in the economic conditions, but not so in explaining the length it takes for each MSA to recover its real GDP.

ACKNOWLEDGEMENTS

First and foremost, I would like to thank my family for supporting me through all aspects of life. I am grateful for the opportunity provided to me and am motivated by their immense work-ethic and positive outlook. I would also like to extend my sincere gratitude to my reader, Professor Manfred Keil. Without you, I would not be the student, researcher, or worker that I am today. I am grateful for all of your feedback and commitment that you have expressed throughout my journey at CMC.

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I. Introduction

The Great Recession of 2007 to 2009 generated significant turmoil in most regional labor markets. However, the increase in unemployment rates was not uniform: some labor markets experienced quite severe disruptions, while others were less affected. By now, most areas have completely recovered from employment losses and added jobs beyond the pre-recession levels (both the U.S. and California reached that level in 2014).

Others have recovered in some dimensions but are still hurting in other aspects economically. Take the 13th largest Metropolitan Statistical Area (MSA),[1] for example. The Riverside-San Bernardino-Ontario MSA is home to over 10% of California's population and has outpaced both national and California employment growth rates following the trough. The area also saw a full recovery to its pre-recession employment levels by 2014, but still remains below its pre-recession level of real per capita GDP. Clearly the jobs in Health, Logistics, and Leisure and Entertainment that have replaced pre-employment in construction and manufacturing, do not have the same value added dimension.

A natural question for a scientist is to investigate the causes for the differences across regions we observe over time; in other words, to do a comparative economic performance study. One immediate candidate might be the increased rate of arrival of Artificial Intelligence (AI) in the form of automation and digitalization. Muro *et al.* (2018), for example, find that jobs which only required low amounts of digital skill decreased from

[1] The U.S. has some 390 MSAs, typically containing one or two counties. New York is the largest, with the Greater Los Angeles area being second. California places four MSAs in the top 20 ranked by population: Los Angeles-Long Beach-Santa Ana, San Francisco-Oakland-Hayward, Riverside-San Bernardino-Ontario, San Diego.

56% of jobs in 2002 to only 30% in 2016. This hints strongly at a sectoral shift in labor demand. While the most recent national unemployment rate levels of 3.8% (February, March 2019) suggest that we have reached full employment, certain industries, such as manufacturing and construction, have failed to recover to their pre-recession employment levels in aggregate data. This effect has been magnified in areas where a large number of jobs relied on manual labor until recently, but have since been cut, outsourced, or automated. Since many of these jobs were occupied by male workers prior to the recession, some have referred to the Great Recession as a "mancession." This has had effects beyond economics and was to a large extent responsible for President Trump's election in 2016 (on this see Autor *et al*., 2016).

Let's take a closer look at the Youngstown-Warren-Boardsman MSA which is often cited by both political parties. Despite increases in overall national employment and in manufacturing since the end of the Great Recession, the Youngstown, OH/PA MSA has seen employment losses during the recovery period beginning in 2010.[2] The Youngstown MSA is not alone: certain census regions, such as New England and Middle Atlantic, have seen net-losses during the post 2010 recovery period (Abel and Deitz, 2019).[3] Compare this to the national level, where data from the Current Establishment Survey (CES) shows a loss of roughly two million jobs in manufacturing from December 2007 to June 2009.

[2] Long, Heather. 2019. "From $22 an hour to $11: GM job cuts in Ohio show a hot economy is still leaving parts of America behind." *Washington Post,* March 5. https://www.washingtonpost.com/business/economy/from-22-an-hour-to-11-gm-job-cuts-in-ohio-show-a-hot-economy-is-still-leaving-parts-of-america-behind/2019/03/05/241b2784-3b80-11e9-a2cd-307b06d0257b_story.html?noredirect=on&utm_term=.e26f38ed46e1.

[3] Jaison R. Abel and Richard Deitz, "Where Are Manufacturing Jobs Coming Back?," *Liberty Street Economics* (blog), Federal Reserve Bank of New York, February 6, 2019, https://libertystreeteconomics.newyorkfed.org/2019/02/where-are-manufacturing-jobs-coming-back.html.

The industry continued with the bloodletting even after the end of the recession until March 2010. By now (March 2019), it has recovered close to 900,000 of these lost jobs.

Accounts of this type of industrial change are not just topics in academic journals. Many have made it into the popular press: Long (2019), for example, gives a detailed account of recent job cuts from automotive manufacturer General Motors (GM) in Ohio:[4] roughly 5,400 employees have been laid off as GM has scaled back production, leaving many relatively low-skilled workers looking to replace wages of around $22 an hour with generous benefits. The demographics of these individuals—mainly less educated workers that have been employed in the same manufacturing jobs for much of their careers—do not provide much opportunity for mobility. Moreover, only about 30 percent of qualified individuals have enrolled in *Trade Adjustment Assistance,* the federal government's marquee retraining program. The situation in this Ohio/Pennsylvania MSA is not atypical: roughly 25% of all MSAs have lost manufacturing jobs since 2010. Clearly individuals are either stuck with lower paying jobs[5] or are trying to train themselves to work in industries that require higher skill levels. The bottom line is that industrial change has created variation in employment patterns as a result of automation, globalization, and changes in demand.

The first publication to seriously consider the effect of sectoral changes on unemployment and the natural rate of unemployment was Lilien (1982). Theoretically, unemployment rates can be separated into movements in the natural rate and cyclical unemployment (the difference between the natural rate and the actual unemployment rate).

[4] Long, Heather. 2019 (see footnote 2 for full citation).

[5] Long (2019) mentions that these individuals most often click on job postings with an average salary below $35,000.

While we can observe the actual unemployment rate, the natural rate is a theoretical construct that has to be estimated. Unfortunately this is difficult to do in practice and relies on a model of the labor market.

Building on previous work of Lucas and Prescott (1974), Lilien (1982) derives a model of the natural rate of unemployment (full employment unemployment rate also called NAIRU) which suggests that as much as half of the variance of unemployment over the postwar period 1948-1980 can be attributed to fluctuations of the natural rate. This has important economic policy implications since expansionary monetary and fiscal policies typically only reduce cyclical unemployment. To lower the natural rate, more specific labor market policies, such as retraining, better matching, changes in unemployment insurance generosity, etc. are necessary. Hence it is important to have a good measure of the natural rate. The current policy debate in Washington is indicative of the difficulty of knowing and understanding the natural rate: President Trump is urging the Federal Reserve to further stimulate the economy through lowering interest rates, while the Federal Reserve, until very recently (December 2018), seemed to believe that we are now at the natural rate of unemployment.

Lilien's (1982) measure of variation in sectoral employment shows a distinct spike during the OPEC I oil crisis of 1973-1975. During this recession, many jobs in manufacturing and especially in the automobile industry were lost, while mining and oil extraction benefitted from the higher oil prices. It is said that the Houston Chronicle was the second most read newspaper in Detroit. This difference in employment variation by industry as the main motivator for Lilien's original work. However, different from the post-OPEC I period, AI and automation will play a more important role in the future.

Lilien concludes that an increase in dispersion—or shifts of employment between industrial sectors—results in an at least temporary elevated national natural rate of unemployment brought about by slow adjustments of labor to these changes. The subsequent four recessions (double dip recessions, the end of the Cold War recession, and the dot-com bust at the turn of the millennium) did not generate a similar increase in the dispersion measure, which explains why Lilien's measure did not receive much attention beyond its original success (by the latest count, it has been cited 1,484 times in the academic literature).

The Great Recession and the "Not So Great Recovery" have revived the discussion about mismatch. Appleton (2013) showed that sectoral employment variation explained a significant amount in national and state unemployment levels during the Great Recession and the next few years, and that Lilien's dispersion measure spiked during that time period. Others, e.g. Estevão and Tsounta (2011), use a different measure of mismatch to analyze unemployment rate differences by state, but employ the Lilien metric as a robustness check. Sahin *et al*. (2012) quantify how much of the rise in unemployment in the Great Recession is due to an increase in mismatch and find increased mismatch across industries accounts for 0.6 to 1.7 percentage points of the overall increase. Unfortunately the authors only include data up to 2010 and their analysis does not disaggregate data beyond broad geographical regions. To my knowledge, no one has worked with Lilien's concept at the MSA level.

The purpose of this paper is to analyze whether Lilien's variation measure can explain regional differences in the severity of the recession and for the time it took to recover from the shock. Variation in regional unemployment rates was at a level not seen since the OPEC I oil crisis, and even persists to this day although to a lesser extent as the distribution becomes more compressed. Of particular interest will be the changes in the regional unemployment rate resulting from the national shock coupled with a continued structural shift away from many low-skilled manual labor jobs in some regions. In this thesis, I create Lilien's standard deviation measure of employment—the dispersion in industrial composition— for all MSAs with more than 100,000 private employees. I will then look for the effect of this churning on the depth of recession in these MSAs.

The thesis proceeds as follows: section II presents a short summary of the relevant literature. This is followed by a description of all relevant data. The two sections to follow describe the empirical strategy and then discuss the results and implications. A final section concludes.

II. Literature Review

There are two papers that are central to the analysis and specifications here, both of which try to construct measures to capture regional variations of the recession. The first is Arias *et al*. (2016) who generate an economic conditions index for the top 50 MSAs dating back to 1990. The authors use a dynamic factor analysis model (see, e.g. Stock and Watson, 2019; 629-38) with 13 factors. They then analyze this index to date peaks and troughs of the last three national recessions for each of the top 50 MSAs; availability of data limits the sample period to the post-2000 observations. Their findings indicate large variation in the depth of recessions between metropolitan areas, even within the same state. The results strongly suggest the need for analyzing the recessions at a more granular geographic level than at the state level. To clarify, I will take the Arias *et al.* (2016) data as given and use it as an alternative measure for the severity of the regional recession. In the analysis below, I will utilize the maximum fall in the economic conditions index in each period of the last two national recessions as a proxy for the depth of recession that each MSA experienced.

The second paper is by Estevão and Tsounta (2011), which was mentioned earlier while introducing the Lilien (1982) work. This IMF study looks at the effect of skill mismatch in each state on the increase in structural unemployment. The major finding is that increases in skill mismatches coupled with inelastic housing market conditions are associated with higher state unemployment rates during the Great Recession. To capture these characteristics, housing price indices are utilized to represent housing market conditions of each state, and the percentage of the population age 25 and older with a high school diploma is used to proxy differences in human capital levels. I will extend their analysis to the MSA level to capture further the determinants of the severity of labor market disruptions during and following the Great Recession.

In the following sections of the literature review, I describe background work on the development of some concepts surrounding the natural rate hypothesis that is relevant to this thesis.

II.1 Natural and Cyclical Rates of Unemployment

Most economists agree, and have done so for quite some time, that unemployment can be separated into various categories. A crude classification, typically first encountered during a Principles of Economics course, divides seasonally adjusted unemployment into frictional, structural, and cyclical unemployment. The natural rate of unemployment is a theoretical concept that attempts determine the part of the unemployment rate that will persist even at full employment ("full employment unemployment rate"). In other words, it is the equilibrium rate of unemployment. While not generally accepted, between two-thirds to three-fourths of economists believe in its existence (Fuller and Geide-Stevenson, 2003). To make matters more complicated, the natural rate is not constant and depends on a variety of factors.

To make the discussion operational, consider the following decomposition of the unemployment rate into two parts: a portion that exists when the economy is at full employment and a cyclical portion:

$$UR_t = \overline{UR} + (UR_t - \overline{UR}) \tag{1}$$

where $\overline{UR}$is the natural rate of unemployment, and $(UR_t - \overline{UR})$ represents the rate of unemployment due to cyclical factors. Note that it is possible for cyclical unemployment to be positive and negative.

The term "natural rate of unemployment" was first coined by Friedman (1968). The natural rate of unemployment, as he defines, is the level of unemployment that could not be pegged by monetary policy, and exists in the long run due to imperfections and frictions in the labor market.

Phelps (1967), independently from Friedman, created a model of the natural rate of unemployment. Silva (2011) notes that Phelps presents a macrodynamic model in which an optimal path of the employment level of the economy is derived through the maximization of a dynamic social utility function by the fiscal authority. The model is derived from the Phillips curve tradeoff, where, in the dynamic version, the actual rate of unemployment would converge to the equilibrium rate when the actual rate of inflation equals the expected rate of inflation. Friedman's concept is similar, and while he does not give a formal model in his paper, the concept could be described as follows:

$$\Delta p_t = \Delta p_t^{\ e} - \lambda(UR_t - \overline{UR})$$

where *p* is the log of the price level and *e* indicates expectations.

This type of equation is often referred to as the "Expectations Augmented Phillips Curve" (EAPC).[6] In principle, the EAPC can be estimated under the assumption of backwards looking (e.g. adaptive or static) expectations, and if we heroically assumed that the natural rate was time invariant. The natural rate could also be derived if we at least knew for which time periods the natural rate was approximately constant. Regardless, and under the assumption of static expectations, the EAPC indicates that inflation will accelerate if the unemployment rate is below the natural rate. As a result of this insight, the natural rate is also referred to as the Non-Accelerating Inflation Rate of Unemployment (NAIRU). Note that there are two simple conditions under which you can observe the natural rate: (i) expectations are correct, and (ii) the unemployment rate does not change.

Hall (1979) expands on the model of the natural rate by specifying, under general conditions, factors that influence the level of the natural rate. In his model, the steady-state level of unemployment is derived by assuming an equal amount of inflow and outflow into the unemployment pool, and a labor force that is not growing. In such an economy, you can decompose movements in and out of unemployment by the rate of individuals finding jobs (percent of unemployed finding a job during a time period, *f*) and job separation rates (percent of employees losing a job during a time period, *s*):

[6] The original Phillips Curve did not contain expectations. For that matter, it was a relationship between nominal wage increases and the unemployment rate. Moreover, it did not use annual data but instead averaged values over parts of the business cycle.

$$\frac{U}{L} = \frac{1}{1 + f/s} \tag{2}$$

where U is the number of unemployed, and L is the labor force.[7]

Here the equilibrium unemployment rate is determined by factors that influence the ratio of the job finding to job separation rate. Note that this ratio can be the same both for high and low rates of job separation/finding. As a result, the equilibrium unemployment rate is seen as a function of sectoral shifts (change in the composition of demand among industries or regions), mismatches in wages or skills, unemployment insurance parameters, mobility, labor laws, job training programs, and other demographics that may affect the length of employment or unemployment an individual in the labor market may face.

Relevant for my discussion of employment variation during and following the Great Recession is the fact that job finding rates are not high for all participants in the labor market even during recent low levels of overall unemployment. Elaborating on their work (Autor *et al.*, 2016) cited earlier, David Autor, in a podcast on *Freakonomics Radio* (January 25, 2017), details how globalization has affected manufacturing jobs. In one example, he outlines that when it comes to finding a new job during and following the Great Recession, certain sub-sections of employees working in manufacturing, such as assembly line workers, may have had a harder time finding new employment in other sectors than others, for example employees working in the human resource section of manufacturing firms. Hence even within a sector, the ability for find a new job after being laid off depends on the level and qualification of the individual.

[7] For a simple derivation, see Mankiw (2016).

II.2 Demographic Shifts and the Unemployment Rate

Demographics influence both job separation and job finding rates. Younger workers have a higher rate of job finding and job separation rates relative to older workers. What would happen if there was an increase in the share of labor of younger people? Since younger workers have significantly higher unemployment rates, it would suggest that the overall natural rate would be affected when the share of younger workers increase. What would cause such a shift? The baby boomer generation comes to mind (increased participation of women in the labor force is also a possibility, but females have equilibrium rates of unemployment that are similar to those of males, if not lower).

Shimer (1999) suggests that demographics in general can affect the NAIRU. In this instance, he attributes much of the fall in the unemployment rate in the 1990s to a compositional change in demographics, namely that of a decreased share in young workers (ages 16-24).[8] Demographics may also affect labor force participation rates. Note that the early cohort of baby boomers turned 65 in increasing numbers around 2015 and while they were still part of the population, they started to retire at increasing rates. This may explain part of the dramatic decrease in the labor force participation rate following the Great Recession, which is also significantly below the peak observed at the early part of the millennium. In addition, an increasing number of younger people remains in school longer. Looking at participation rates of 25 to 54 year olds, the drop is much less pronounced.

Sherk (2014) finds that holding demographic changes constant—such as aging and the level of education—explains less than a quarter of the drop in labor force participation.

[8] This is under the assumption that changes in labor force share does not alter the disaggregated unemployment rates of the subset, but he finds some evidence against this assumption empirically.

This finding attributes a portion of the remaining drop in labor force participation to increased disability claims as well as stalled job creation. The latter interpretation provides, in part, the inspiration for the analysis to follow.

II.3 Variation in Structural Employment

How does Lilien's (1982) work fit into this discussion? The author uses sectoral variation to show that the NAIRU increased in the 1970s. Building on the work by Lucas and Prescott (1974), which derives the equilibrium unemployment rate from the assumption that labor is exchanged in many spatially distinct markets and that labor mobility between markets is time consuming, Lilien shows that random fluctuations of product demand induce fluctuations of labor demand. This subsequently leads to temporary wage differentials between markets. These wage differentials result in shifts of sectoral labor supply as workers move towards higher paying jobs. This process is time consuming, thus a positive level of unemployment persists in stationary equilibrium. Lilien rejects Lucas and Prescott's assumption that market-specific demand fluctuations have a constant variance over time, which would yield a constant equilibrium unemployment rate.

Lilien constructs a variable σ to capture employment variation between sectors (more on this below). He then includes this measure as an explanatory variable to predict the unemployment rate using in addition to control variables such as lagged unemployment, and a measure of unanticipated money growth first used by Barro (1977).

II.4A Arguments against Structural Change

The literature is split on the idea that the effects of the Great Recession are structural rather than cyclical. Lazaer and Spletzer (2012) and Rothstein (2017) both posit that their analysis point primarily to cyclical changes. Lazaer and Spletzer find that despite initially increased mismatch during the recession, it decreased over time. The authors therefore find that the observed patterns are consistent with unemployment being caused predominantly by cyclic phenomena.

Rothstein focuses on wage trends and finds little evidence of significant wage pressure. The author admits, though, that his focus is exclusively on the very short run, the time period between 2007 and 2015, and therefore does not address potential longer-run structural changes.

III. Data Description

The current section deals with various aspects of the construction of the main variables used in my analysis.

The initial task was to replicate Lilien's variance measure of employment growth, and then to extend it to the current period. Monthly employment by sector by MSA[9] is based on CES (establishment) data produced by the Department of Labor/Bureau of Labor Statistics (DoL/BLS). Monthly data was converted to annual figures to correspond to the

[9] The CES reports New England areas by New England City and Town Area (NECTA), which are analogous to MSA, so these divisions are used in place of MSAs.

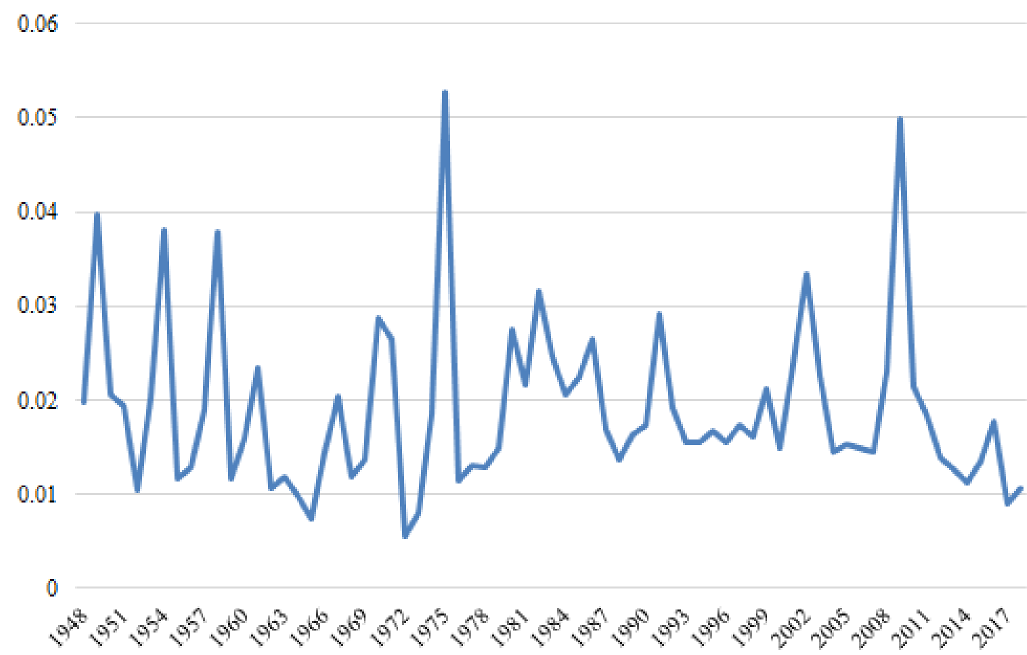
methodology used by Lilien (1982). The measure, derived first nationally and then by MSA, is defined as follows:[10]

$$\hat{\sigma}_{jt} = \left[\sum_{i=1}^{11} \frac{x_{ijt}}{X_{jt}} \left(\Delta log\, x_{ijt} - \Delta log\, X_{jt}\right)^2\right]^{1/2} \tag{4}$$

where x_{ijt} is employment in industry i in MSA j at year t and X_{jt} is the aggregate employment for that MSA.

Figure 1 displays the employment growth variation for the national U.S. economy.

Figure 1: Dispersion of Employment Growth, United States, 1948-2018



Note that the four recessions following the OPEC I recession resulted in much less churning. It was not until the Great Recession that the national economy experienced a similar spike.

[10] Only 44 of the MSAs with over 100,000 total private employees report figures for the Mining and Construction industries.. When only 9 sectors are available, the calculations are adjusted to only include these sectors.

Figure 2 shows the distribution of σ by MSA. Since it is positively skewed (skewed to the right), the implication is that there are a few MSAs that experienced massive churning during the 2008 recession, while most MSAs were less affected. However, since the mode is around, there is a significant number of MSAs that saw a substantial amount of sectoral employment growth differences from the overall employment growth in the MSA.

Figure 2: Histogram of Maximum σ, MSAs, Great Recession

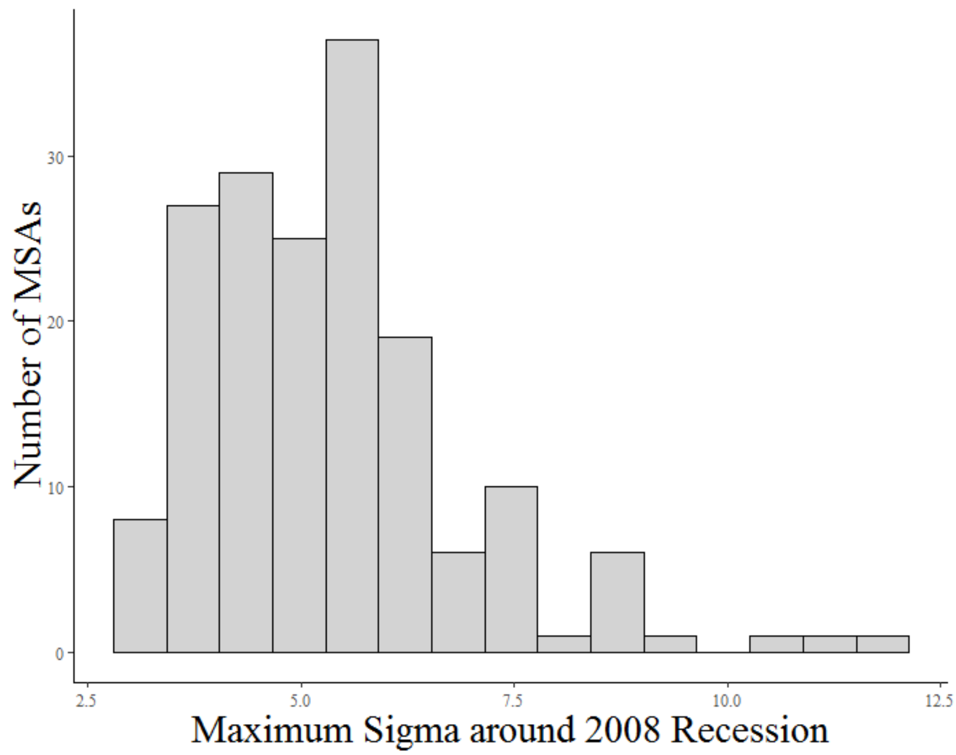
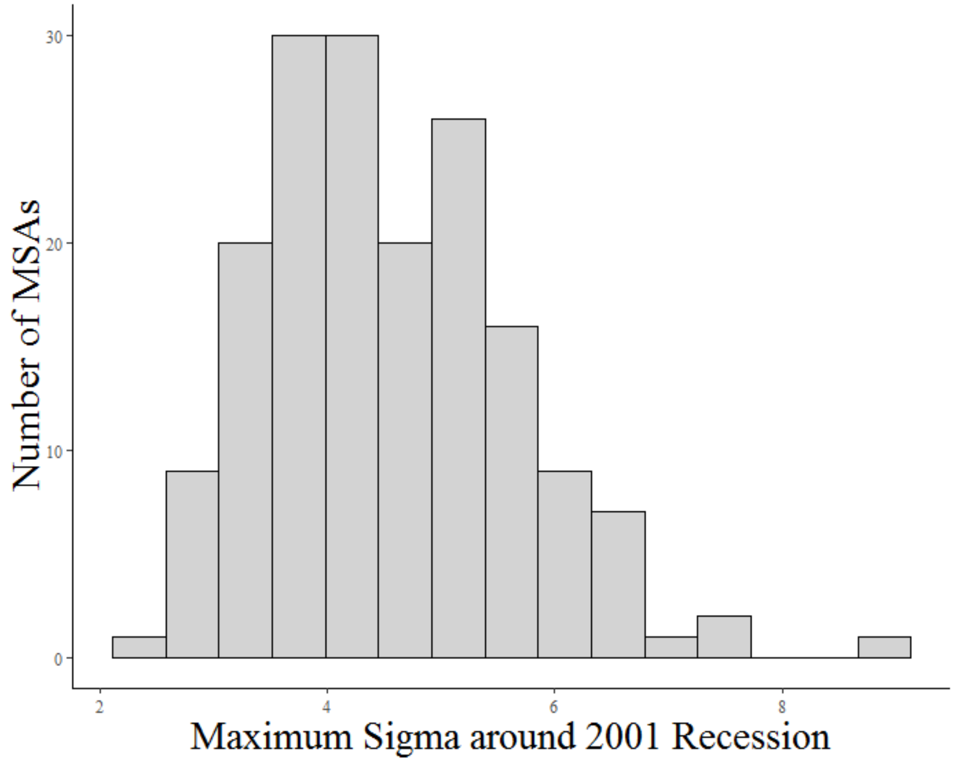


Figure 3 repeats the exercise for the 2001 recession. It becomes immediately clear that there was significantly less churning during the earlier recession:[11] there are few MSAs that experienced an employment dispersion measure greater than 6.

[11] This would be even more obvious if I had chosen the same scale for the horizontal axis.

Figure 3: Histogram of Maximum σ, MSAs, dot-com Recession



My main hypothesis is that a greater degree of employment growth variation results in a deeper recession due to mismatches in the labor market, which then results in higher job separation rates and lower job finding rates. The regression coefficient on the variation measure will therefore be our parameter of interest.

The next step was to settle on local measures for the severity of a recession next, which will be the LHS variable in the analysis below. The first subsection outlines the construction of the primary measure for the depth of recession: the increase in the unemployment rate by MSA during each of the two recessions used for the analysis. The sample period is limited by the availability of MSA data: employment data is published for the post-1990 period. We did not analyze the 1990/1991 recession since some of the RHS variables, such as real GDP, are not available prior to 2000, and also since the 1990/1991 recession may have started slightly earlier in some MSAs.

This section describes the sources and implications of the data involved in calculating this measure, and displays evidence for the importance of placing emphasis on the 2008 recession at the MSA level. The second subsection outlines the calculation of an alternative measure which I then use as a robustness check for my result. The fall in the "Economic Conditions Index," a metric constructed by Arias *et al.* (2016) for the 66 largest MSAs. We use this variable as an alternative to the rise in unemployment rate for the depth of recession to check the robustness of our conclusions below.

III.1 Change in the Unemployment Rate

Lilien (1982) establishes that the standard deviation of employment by industry has a significant effect on the natural rate of unemployment. Estevão and Tsounta (2011) use a skill mismatch index similar to Lilien's variation measure as a robustness check for the effect on the natural rate of unemployment at the state level. The authors find that the results hold using both measures.

Following Lilien (1982) I utilize a standard deviation measure in this paper, as the industries have a wide variety of skilled jobs within each sector (for example, health and education is listed as a high-skilled sector, although home health aides, the largest sector of health care services, have an average salary of $12/hr). MSAs vary widely in size (from 55,000 to 20.3 million in population). Our analysis below will only consider MSAs with a population of over 100,000 private employees (or 2.8 million employees for the initial analysis of the top 20 MSAs). While this cutoff point is somewhat arbitrary, I believe that there should be a critical mass of workers to avoid too much noise in the data being generated by the behavior of single employers.

The main idea behind this measure of "churning" originally was to show that movements in between sectors has a significant effect on the natural rate of unemployment. Here I pursue a different aim: I will use σ as a RHS variable to explain differences in the depth of recessions by region. The analysis utilizes a cross-sectional approach as opposed to a panel data, since I focus on the behavior of MSAs during a recession rather than analyzing its economy over time.

I will use several measures to capture the severity of the recession experienced by each MSA in my sample for the years surrounding the 2001 and 2008 downturn. The first metric is the difference between the maximum unemployment rate and the pre-recession minimum. Monthly unemployment rates for each MSA are collected from the Local Area Unemployment Statistics reported by the BLS and are seasonally adjusted using the standard X-12 methodology available in most statistical packages.[12]

Several relevant studies (e.g., Arias *et al.*, 2016; Estevão and Tsounta, 2011) also look at a measure of housing supply elasticity as an explanatory variable for the depth of recession experienced by local economies. Typically they find that housing markets that experienced large decreases in housing prices seem to have had a significant effect on increases in unemployment rates. In this thesis, housing prices are mainly used as a control variable. The data we used here is provided by the Federal Housing Finance Agency. Specifically, I focus on the (seasonally adjusted) quarterly all-transactions indexes by

[12] The X-12 s a seasonal adjustment algorithm developed by the U.S. Census Bureau. The X12 procedure seasonally adjusts monthly or quarterly time series. The procedure makes additive or multiplicative adjustments and creates in output data set containing the adjusted time series and intermediate calculations as outlined by Jackson and Leonard (2000).

MSA. Next the data is converted into quarterly growth rates then annualized. Finally, the largest decrease (in absolute terms) is selected for the period surrounding the recession.[13]

Another control variable to consider is the level of human capital present in the MSA. To measure education, I am using data from the American Community Survey (ACS)/U.S. Census Bureau. The ACS provides a 5-year estimate for 2009 educational attainment and I employ it for my analysis since this measure is relatively constant over time. Specifically I calculate the level of education for each MSA as the percent of the population 25 years and older with a high school diploma.[14]

Another control variable to explain changes in the unemployment rate, also used by Estevão and Tsounta (2011), is the real GDP growth rate. This factor is introduced in reference to Okun's Law. The dynamic version of this well-known relationship in macroeconomics relates the change in the unemployment rate to the difference between real GDP growth rates and potential GDP growth rates, using some restrictive assumptions. Since I wanted to use the same control variable, I collected annual real GDP (chained to 2009 dollars) growth rates provided by the U.S. Department of Commerce/Bureau of Economic Analysis (BEA). To correspond to observations in my cross-sectional analysis, I calculated the maximum percentage fall of real MSA-GDP around the recession points. The BEA only started to produce real GDP by MSA relatively recently and only data back to 2001 is available to the public. Hence I was only able to use the variable for the 2008 recession.

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[13] The years 2005 to 2010 were included in the sample Great Recession sample to allow for variation in time that the housing market hit each MSA. The years 1998 to 2002 were included in the 2001 recession.

[14] The ACS only goes back until 2005, but for the purpose of this analysis the human capital rate is assumed to be roughly time invariant for each MSA.

Table 1 provides summary statistics for the 172 MSAs in my sample.

Table 1: Summary Statistics of Maximum Unemployment Rate Sample

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
σ (2008)	172	5.4	1.5	2.8	11.5
Unemployment Rate Change 2008	172	6.2	2.3	2.1	19.2
HS Graduation Rate	172	85.7	5.1	59.5	93.4
Housing Index Decrease 2008	172	-14.7	12.4	-64.9	-2.7
σ 2001	172	4.5	1.1	2.5	9.0
Unemployment Rate Change 2001	172	3.3	1.2	1.4	10.7
Housing Index Decrease 2001	172	-0.8	3.8	-18.5	7.8
Real GDP Fall 2008	172	-4.0	3.4	-27.7	1.7
Real GDP Fall 2001	172	1.4	2.8	-11.7	9.2

σ, which in the analysis below is expressed in percentage points, ranges from as low as 2.8% to 11.5% with a mean of 5.4% during the Great Recession. As shown in the histograms above, it is lower, on average, for the 2001 recession. Similarly, increases in the unemployment rate are higher during the Great Recession than during the dot-com episode. Note that the observation for the maximum decrease in the house price index fall is positive. The housing market did not appreciate as much before the 2001 recession and therefore did not even fall in several of the MSAs. In these instances, the smallest increase in the house price index is used.

III.2 Economic Conditions Index

Arias *et al.* (2016) create an economic conditions index for the 50 largest MSAs in which each index is derived from a dynamic factor model based on twelve underlying variables capturing various aspects of economic activity. The model series includes labor market variables such as, average weekly hours worked, the unemployment rate, goods and service producing employment; other economic variables such as, construction permits for residential buildings, measures of income and wages; and investment variables including the return on average assets and the net interest margin. The dynamic factor model is indexed to gross metropolitan product to create an economic conditions index, from which the authors use date peaks and troughs of recessions. As a robustness check, the economic conditions index constructed in that paper is used as an alternative measure of the depth of recession. The indexes are now available from the Federal Reserve Economic Data by the Federal Reserve Bank of St. Louis. Sixteen MSAs have been added, thus the largest 66 MSAs are included in this analysis. The monthly series are seasonally adjusted from February 1990 to September 2018, and are indexed to February 1990. The depth of recession measure is constructed by subtracting the pre-recession maximum level of the index from the recession trough to gather the maximum fall for each recession. The summary statistics for the 66 MSAs in this sample may be seen below in Table 2. All other variables listed in Table 2 are as previously defined.

Table 2: Summary Statistics of Economic Conditions Sample

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
ECI Fall 2008	66	12.0	5.5	4.7	37.3
σ 2008	66	5.3	1.5	3.0	11.5
ECI Fall 2001	66	7.6	4.1	2.1	27.3
σ 2001	66	4.1	1.0	2.5	9.0
HS Grad Rate	66	85.9	3.5	71.4	92.5
Housing index fall 2008	66	-16.1	12.2	-54.9	-3.3
Housing index fall 2001	66	1.1	3.1	-10.0	7.8
Real GDP growth rate, Fall 2008	66	-4.0	2.7	-11.6	0.8
Real GDP growth rate, Fall 2001	66	1.1	2.2	-6.2	6.6

Note that the fall in the economic conditions index, is measured in absolute terms in Table 2 while the house price index fall is measured in its real value. The conditions index is measured in percentage points, such that the MSA with the largest fall experienced a drop of 37.3 percentage points in the index. The statistics for σ and the controls are largely similar to those for the larger sample, indicating that these larger MSAs are representative of the majority of the country.

IV. Data Analysis

A stylized fact of U.S. recessions is that their effect varies substantially across regions. However, the extent to which this is true depends on the specific episode, and in particular how great the differences in industrial composition, e.g. mining versus manufacturing, construction, etc., are. This fact is one of the major takeaways from both Lilien (1982) and Estevão and Tsounta (2011). However, the purpose of their analysis was to show that the standard deviation of employment by industry contributes to variation in the structural rate of unemployment. As pointed out above, this fact has major economic policy implications.

Here I will use the standard deviation measure to determine the extent to which the churning between industries has an effect on the depth of the recession, meaning do large industrial changes in the local area result in a more severe regional recession. To investigate this, I will use a cross section of MSAs, rather than a time series of U.S. data. Initially I decided to restrict my sample to the twenty largest MSAs. These are MSAs that had a population of at least 2.8 million. I felt that while the sample size is small, it will give us an initial indication of the extent to which my hypothesis holds. The next step is to apply the initial insights to a larger sample of 172 MSAs, where these were chosen to include those areas that employ at least 100,000 people.[15]

The initial model utilizes the following specification:

$$\Delta UR_i = \beta_0 + \beta_1 \sigma_i + \beta_2 X_i + \epsilon_i \tag{5}$$

where ΔUR_i is the difference between the peak unemployment rate reached during the 2007-2009 recession and the pre-recession unemployment rate (this is done for both the Great Recession and dot-com recession), σ_i is the maximum standard deviation of sectoral employment at MSA *i* during the respective recession, X_i is a vector of MSA characteristics which includes a measure for education, housing market conditions, and real GDP growth for MSA *i* during the recession, and error term ϵ_i with the usual characteristics.[16]

As always, the main concern with the econometric specification is that there are omitted variables that drive these results. Geography, socio-economic conditions, culture,

[15] Constructed as the sum of all available industries.
[16] I allow for heteroskedasticity robust standard errors here.

etc. come to mind. To better control for the time invariant characteristics that each MSA may have over the depth of recession, a two period panel regression is utilized for the two recessions in the sample. In essence, I take the difference of the two recession episodes, thereby eliminating the influence of MSA specific characteristics that remained constant between 2001 and 2008. This is the equivalent of a panel regression with MSA fixed effects.

The two-period regression uses the following specification:

$$\Delta UR_{08} - \Delta UR_{01} = \beta_0 + \beta_1(\sigma_{i_{08}} - \sigma_{i_{01}}) + \beta_2(X_{i08} - X_{i01}) + \epsilon_{08} - \epsilon_{01} \quad (6)$$

where the variables are the same as in (5), but X_{it} is a vector of characteristics that includes a measure for housing market conditions, and real GDP growth for MSA *i* during the recession. I left the high school graduation rate out of this specification since it is approximately constant over the two recession periods.

IV.2A Alternate Measures of Depth of Recession

The index constructed in Arias *et al.* (2016) is used as a robustness check for the depth of recession. Under this hypothesis, the maximum depth of recession classified by the largest drop in the economic conditions index would be adversely affected (drop further) in the presence of large churning between industries. The specification are similar to equations (5) and (6), and are specified as follows:

$$Y_{it} = \beta_0 + \beta_1\sigma_{i_t} + \beta_2 X_{it} + \epsilon_t \quad (7)$$

$$Y_{i08} - Y_{i01} = \beta_0 + \beta_1(\sigma_{i_{08}} - \sigma_{i_{01}}) + \beta_2(X_{i08} - X_{i01}) + \epsilon_{08} - \epsilon_{01} \quad (8)$$

where Y_{it} is a measure of the depth of recession in MSA i during recession period t, σ_{i_t} is as defined in equation (5), and X_{it} is the same vector of MSA characteristics as in equation (5) but excludes a measure for real GDP. When Y_{it} is the drop in the economic conditions index over the recession period, it does not make sense to include GDP by MSA, as the index is calibrated to MSA GDP.

A third measure considered to capture the depth of recession is looking at the number of years it took real GDP to recover during the Great Recession. In conjunction with this measure, the ratio of the 2017 per capita real GDP to the pre-recession maximum per capita real GDP for each metropolitan area is also considered. This measure captures the effect churning has on the length of recovery. In theory, the added time of unemployment corresponding with switching industries (churning) would correspond with a longer period of recession and thus metropolitan areas that sustain large levels of churning would have a lower ratio of current per capita GDP to pre-recession per capita GDP than others. This investigation seeks to identify metropolitan areas that have been adversely affected at a level greater than employment. In some adversely affected areas such as the Inland Empire, employment levels have eclipsed their pre-recession peaks, but per capita real GDP have still yet to recover. This model looks into whether or not increased churning is a factor in this prolonged recovery.

V. Results

MSAs vary in population size from a slightly over 50,000 to nearly 20 million. In the initial analysis, we wanted to focus on areas that are representative of large economic centers.

Choosing the top 20 MSAs at first, this resulted in a cutoff point of approximately 2.8 million in population.

The results from the twenty largest metropolitan areas for model specifications (5) and (6) and some variations are presented in Table 3. Regressing the maximum increase in the unemployment rate on the maximum σ for the two recessions of 2007-2009 and 2000-2001 (columns (1) and (4)), shows that our parameter of interest is highly statistically significant. As expected, the coefficient for the 2008 recession is substantially larger than for the 2001 recession. This suggests that larger variations in σ result in larger variations in the unemployment rate. A one standard deviation increase in the maximum level of σ during the 2008 recession results in an increase of the maximum unemployment rate of approximately 1.4 percentage points. To illustrate the magnitude consider the New York-Newark-Jersey City MSA. Here the one standard deviation increase would have cost an additional 139,250 workers their job by February of 2009.

Adding the control variables for the housing market, education, and real GDP growth (columns (2) and (5)) leads to a small reduction in the σ coefficient and takes away the statistical significance during the Great Recession. This may be in part due to the limited variation in the sample with 20 observations. Education and the housing variable carry the expected signs and are consistent with the findings of Estevão and Tsounta (2011). MSAs that experienced the deepest recessions were those with lower education levels and decreased housing supply elasticity according to Arias *et al*. (2016). Education, though, is not seen as statistically significant. This is unfortunate as education is the one aspect that can be feasibly targeted through policy. Perhaps this is due to the lack of variation in graduation rates between the twenty largest metropolitan areas. The 2001 value for the largest housing price fall is not statistically significant since the housing market only played a minor role during this recession.

Finally σ is interacted with the housing market variable. The coefficient is positive and is statistically significant. This suggests that in the presence of very large falls in the housing market, the effect of σ on the unemployment rate change is not as strong. This would also imply that in situations in which σ played a large role in the increase of the unemployment rate, the housing market was not as significant a factor in the explanation of the change in unemployment rate.

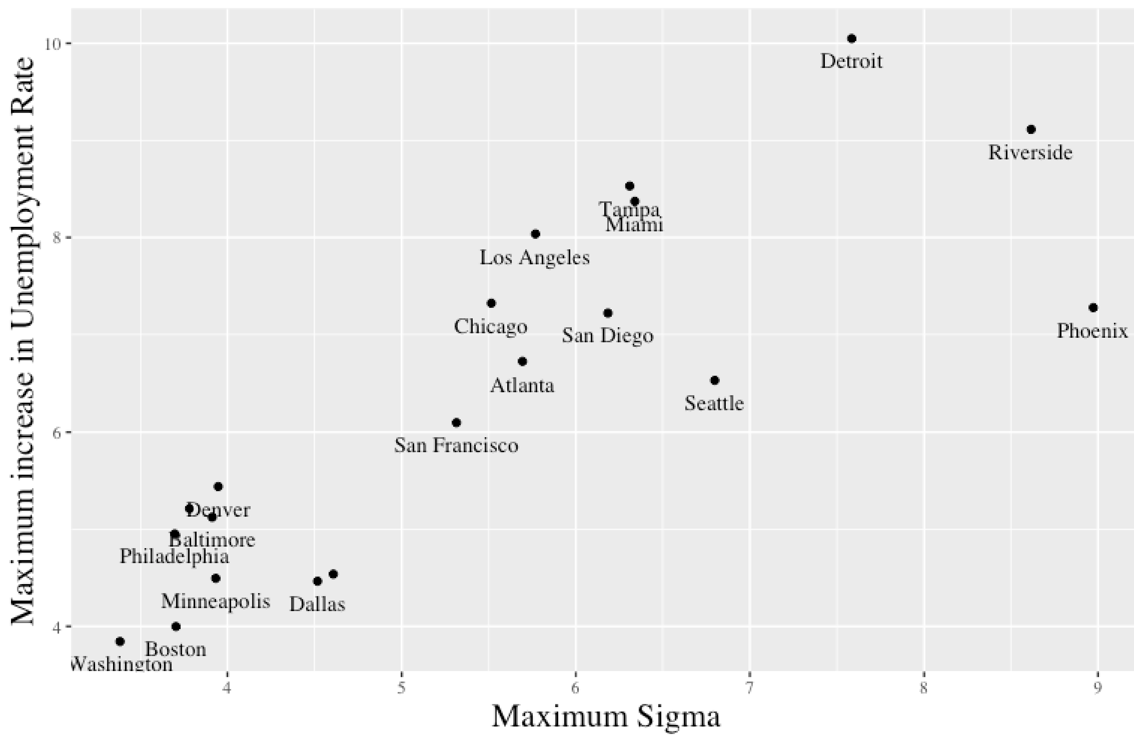
Table 3: Regression Analysis of the Effect of Sectoral Employment Growth Variations on the Change in Unemployment Rate, 20 Largest MSAs

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	2008	2008	2008	2001	2001	2001
σ	0.914***	0.418	0.955**	0.486***	0.482**	0.558***
	(0.193)	(0.328)	(0.368)	(0.180)	(0.203)	(0.165)
Real GDP Fall		-0.210	-0.174		-0.155**	-0.138*
		(0.170)	(0.162)		(0.0650)	(0.0719)
HS Grad Rate		-0.0330	-0.0693		-0.0137	-0.00206
		(0.0605)	(0.0545)		(0.0384)	(0.0456)
Housing Price Fall		-0.0209 (0.0215)	-0.142* (0.0718)		-0.0119 (0.0384)	0.305 (0.303)
*σ*Housing Price Fall*			0.0200*			-0.717
			(0.0105)			(0.0678)
Constant	1.408	5.546	5.943	1.046	0.584	1.166
	(0.928)	(5.636)	(4.906)	(0.842)	(2.833)	(3.579)
Observations	20	20	20	20	20	20
R-squared	0.694	0.749	0.794	0.191	0.332	0.360

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Figure 4 displays the cross-plot corresponding to Column (1). The figure suggests a strong positive relationship between sigma and the increase in the unemployment rate, which is consistent with the regression results.

Figure 4: Unemployment Rate Changes and Structural Change, Top 20 MSAs, Great Recession



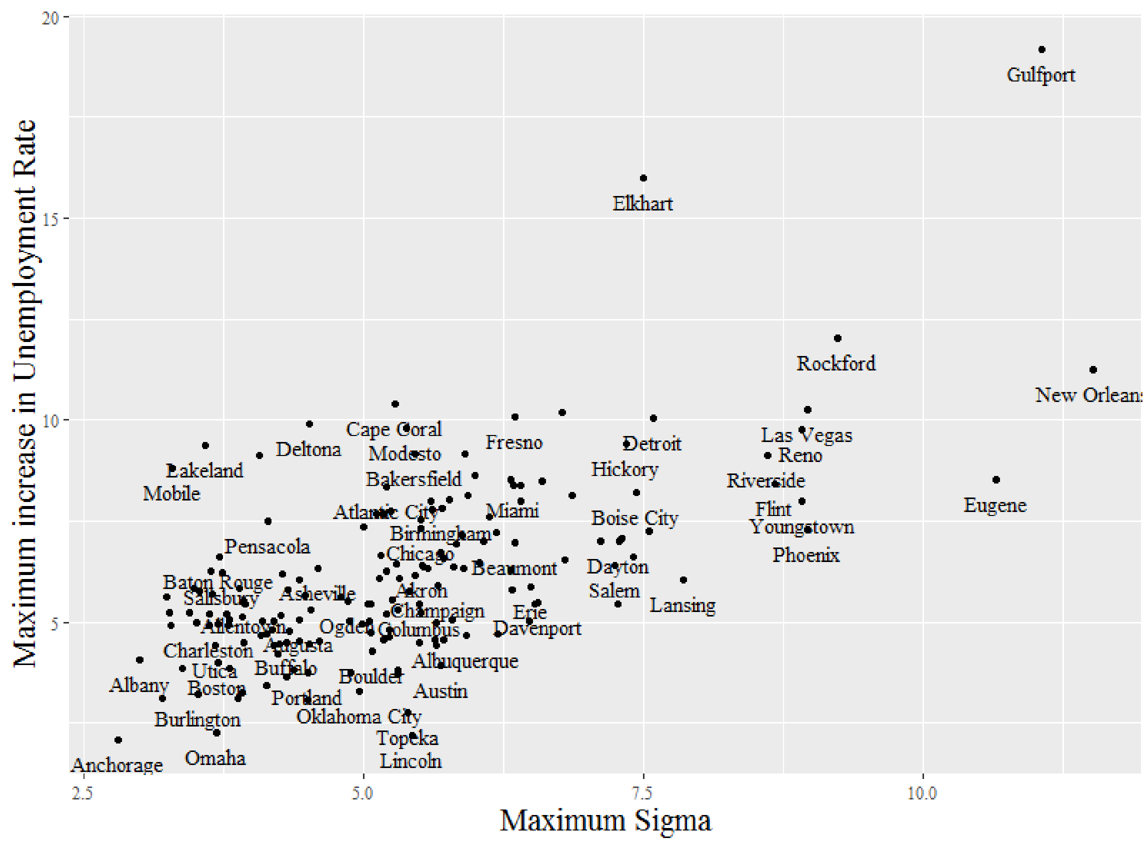
One concern with the result presented so far is that the sample size is quite small. This may also explain the insignificance of sigma in column (2) and of the education variable: there simply may not be sufficient variation across the Top 20 MSAs. To see how sensitive the result are to the chosen sample, the next section expands the sample size to the top 172 largest MSAs (those with an employment level of at least 100,000 workers).

Analysis Using MSAs with 100,000 or more Employees

Table 4 repeats the analysis from above for the larger sample.

The cross-plot of the change in the unemployment rate and σ for the 2008 recession can be seen in Figure 5 below. The figure suggests a positive relationship between the maximum increase in the unemployment rate and the maximum σ. However, there are no controls used to generate this graph. Some outliers can be observed in the cases of Elkhard, IN and Gulfport, MS metropolitan areas.

Figure 5: Unemployment Rate Changes and Structural Change, Top 172 MSAs, Great Recession



After analyzing the results for the top twenty MSAs, those with over 100,000 private employees are utilized to expand the sample size. The results are largely similar in magnitude to those of the top 20 MSAs in the simple regression models. Where things change, though, is in column (2). In the larger sample, both sigma and education become statistically significant.

The one measure from these with substantial policy implications is education. In a recession in which churning went up by two standard deviations in model (2) of Table 4 (an increase of approximately 3 percentage points), the increase in maximum unemployment rate would go up by approximately 1.5 percentage points. In order to mitigate these effects, an increase in one standard deviation of the high school graduation rate (say, going from the national average 85% to 90%) would effectively mitigate about a third of a percentage point in the unemployment rate rise. This may seem insignificant at first glance, but for areas such as the Inland Empire going from its 78% high school graduation rate to the national average could mitigate the losses of half of a percentage point in the unemployment rate, or saving approximately 89,000 jobs.[17]

[17] Using labor force figures from January 2008 from the Local Area Unemployment Statistics reported by the Bureau of Labor Statistics.

Table 4: Regression Analysis of the Effect of Sectoral Employment Growth Variations on the Change in Unemployment Rate, 172 Largest MSAs

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Model 1 2008	Model 2 2008	Model 3 2008	Model 1 2001	Model 2 2001	Model 3 2001
σ	0.924***	0.546***	0.947***	0.377***	0.313***	0.269***
	(0.137)	(0.203)	(0.227)	(0.108)	(0.0756)	(0.0736)
Real GDP Fall		-0.184**	-0.182***		-0.0437*	-0.0405
		(0.0718)	(0.0687)		(0.0262)	(0.0264)
HS Grad Rate		-0.0659***	-0.0640***		-0.113***	-0.110***
		(0.0223)	(0.0210)		(0.0260)	(0.0247)
Housing Price Fall		-0.0516***	-0.212***		0.0222	0.156*
		(0.0124)	(0.0319)		(0.0200)	(0.0813)
*σ*Housing Price Fall*			0.0259***			-0.0274
			(0.00541)			(0.0173)
Constant	1.259*	7.439***	4.990**	1.582***	11.61***	11.52***
	(0.700)	(2.125)	(2.155)	(0.449)	(2.161)	(2.084)
Observations	172	172	172	172	172	172
R-squared	0.394	0.577	0.618	0.119	0.341	0.351

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Analysis Using Economic Conditions Index

Table 5 represents the results for an alternative measure for the depth of the recession. We look at this replacement as a robustness check for our previous results when using the change in the unemployment rate. As previously mentioned, real GDP growth is omitted from these recessions for several reasons. First, the previous regressions contained the growth rate of real GDP as a RHS variable since Okun's Law suggests it as an explanatory variable. Second, the economic conditions index is calibrated to mimic the behavior of real GDP within each MSA.

The results in Table 5 are consistent with the hypothesis that an increase in employment growth variation will lead to an increase in the depth of recession an MSA will face. The impact of the drop in the conditions index is a little more difficult to interpret in real terms since it was constructed using a dynamic factor analysis. However, all specifications indicate a significant effect of σ on the fall in the MSA economic conditions.

Table 5: Regressions of Maximum Fall in Economic Conditions Index

VARIABLES	(1) Model 1 2008	(2) Model 2 2008	(3) Model 1 2001	(4) Model 2 2001	(5) Model 1 2008- 2001
σ	1.879***	1.707***	1.828**	1.567**	1.164***
	(0.518)	(0.626)	(0.834)	(0.635)	(0.369)
HS Grad Rate		0.0923		0.0834	
		(0.144)		(0.141)	
Housing Price Fall		-0.0578		-0.341*	-0.0406
		(0.0674)		(0.175)	(0.0395)
Constant	2.048	-5.901	0.00542	-5.712	2.413***
	(2.510)	(13.43)	(3.376)	(13.13)	(0.768)
Observations	66	66	66	66	66
R-squared	0.286	0.297	0.211	0.271	0.318

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Analysis Using Two-Period Panel Regression

In the two-period panel regression seen in Table 6, the results are similar. All results for sigma remain statistically significant and hold the expected sign with the exception of column (2). The results for σ indicate that an increase (decrease) in the maximum value for σ correspond with an increase (decrease) in the change in unemployment rate when comparing the 2008 recession effects to the 2001 effects. These findings help to mitigate any effects of potential omitted variable bias by removing the effect of any time-invariant characteristics, although are a little less simple to interpret. The results for σ in column (4) would indicate that an increase in the standard deviation of employment by sector from 4 to 5 from the 2001 to 2008 recession would lead to an increase in the maximum unemployment rate by 0.37 percentage points. This would still mean an extra 36,280 people laid off in the New York MSA from the example above.

Table 6: Two period panel regression

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	ΔUR Top 20	ΔUR Top 20	ΔUR Top 172	ΔUR Top 172	ECI Fall	ECI Fall
σ	0.805***	0.213	0.582***	0.371***	1.282***	1.164***
	(0.117)	(0.277)	(0.115)	(0.137)	(0.359)	(0.369)
Housing Price Fall		-0.0416*		-0.0452***		-0.0406
		(0.0225)		(0.0123)		(0.0395)
Real GDP Fall		-0.161		-0.130***		
		(0.128)		(0.0483)		
Constant	2.282***	1.038**	2.439***	1.287***	2.968***	2.413***
	(0.288)	(0.455)	(0.163)	(0.220)	(0.552)	(0.768)
Observations	20	20	172	172	66	66
R-squared	0.592	0.739	0.224	0.403	0.306	0.318

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Analysis Using Time for GDP to Recover

The Great Recession was followed by the "Not So Great Recovery." Since the last recession saw sectoral changes not seen since the OPEC I recession of the early '70s, it is tempting to attribute the slow recovery to workers having to find jobs in industries that are quite different from the jobs they previously occupied. Hence we want to analyze next if it is true that areas that had seen more sectoral changes took a longer time period to recover. It is possible that the housing crisis contributed to this, since workers who lost their jobs may have been unable to move to a new area - meaning mobility may not have been as high as during previous recoveries. This may have been the result of the dramatic fall in housing prices, resulting in properties being “underwater” or in foreclosure.

Table 7 presents our results. The LHS variable in Columns (1) - (3) is the number of years it took each MSA to recover to its pre-recession peak level of real GDP. While we would have liked to use monthly data here, GDP by MSA is only available at an annual frequency. Another weakness of this measure is that some MSAs have yet to recover. Take as an an MSA that peaked in 2006 and fully recovered by 2013. The recovery length in this case is 7 (years). Another MSA may have peaked in 2010 but has not recovered by 2017, the last year for which the BEA has provided estimates of MSA GDP, then that MSA would show a LHS variable of the same length. To overcome data problems of this type, we consider an alternative measure for the length of the recovery in column (4), namely the ratio of per capita real GDP in 2017 to its pre-recession peak.

σ has the expected sign and is statistically significant if we do not include any control variables (column (1)). Adding controls for human capital and the fall in housing prices reduces the size of the σ slightly but does not affect its significance level by much (column (2)). It is only when we include the fall in real GDP that σ is no longer statistically significant.

While, at face value, this result is somewhat discouraging when you search for an explanation, you have to reflect on the meaning of a regression coefficient: it is the partial derivative of the LHS variable w.r.t. the variable under consideration, *ceteris paribus*, or “holding everything else constant”. The fact that σ plays no longer a significant role when we include the fall in real GDP is not surprising, since we know from our earlier results that σ plays an important role in determining the depth of the recession, which we measured by looking at its effect on the maximum increase in the unemployment rate. Indeed, when we perform an auxiliary regression (not shown here) of the depth of the recession on σ, then we find a significant correlation. Hence the interpretation in column (3) must be that σ plays no role in explaining the length it takes for the recovery above and beyond the role it plays in explaining the depth of a recession.

Looking at column (2), we see that for a one standard deviation increase in maximum sigma--approximately 1.5 percentage points--the length of the recovery extends by approximately 14 months, in essence an additional year lost in terms of economic activity.

Column (4) uses the alternative measure for recovery strength, the ratio of most recently available real GDP to the pre-recession peak. Results here are disappointing in that not a single of our explanatory variables appears to have any explanatory power. This may be a good sign for metropolitan areas that foresee large levels of dispersion, as it could indicate that despite facing a deeper recession (as seen with unemployment and economic conditions) the damages in terms of production are not irreparable.

Table 7: Regressions of the Recovery from the Great Recession

	(1)	(2)	(3)	(4)
VARIABLES	GDP Length	GDP Length	GDP Length	PC GDP Ratio
σ	0.947***	0.786***	0.278	-0.00833
	(0.156)	(0.176)	(0.202)	(0.00510)
GDP Fall			-0.495***	
			(0.169)	
HS Grad Rate		0.0478	0.0354	-0.000339
		(0.0595)	(0.0517)	(0.00112)
Housing Price		-0.0692***	-0.0533**	0.00111
Fall		(0.0226)	(0.0224)	(0.000691)
Constant	0.364	-3.866	-1.832	1.078***
	(0.953)	(5.417)	(4.766)	(0.100)
Observations	169	169	169	172
R-squared	0.139	0.179	0.320	0.051

VI. Conclusion

The paper primarily uses variations in employment growth rates to analyze a variety of economic questions. In the past, Lilien's (1982) employment variation measure σ has primarily been used to calculate changes in the natural rate of unemployment. Here, instead, the effect of variations in σ is used to explain differences in the depth of recessions across different regions. Specifically, we are interested on assessing the effects of churning between industries to explain the impact on other variables. Regional (MSA) variation in the severity of the downturn is analyzed through differences in industrial composition within each region. The U.S. MSAs generate a richness in this type of analysis since they vary from high tech, to mining intensive, to manufacturing heavy, etc.

The specific policy implications of a large value of σ are beyond the scope of this analysis. MSAs have little control over real GDP growth within their location. However, higher human capital rates can diminish the effect of industrial composition in a variety of ways, both directly and indirectly. Here we are primarily interested in the effect of employment growth variations. Controlling for human capital, housing market conditions, and real GDP growth--relevant measures in capturing variation in depth of recession in accordance with Estevão and Tsounta (2011) and Arias *et al.* (2016)--the effects of an increase in sigma has a significant effect on a number of different measures of the depth of recession.

The research strategy of this thesis was to begin the analysis with the 20 largest MSAs, since these are locations with a population greater than 2.8 million. While this is a small sample size, most readers would be familiar with these areas since they include the Greater New York, Greater Los Angeles, Chicago, Houston, San Francisco, etc. These locations were therefore used first to assess the effect of σ on the increase in the unemployment rate during the two most recent national recessions, namely those of 2001 and 2008. While the initial results were encouraging in that the effect of σ was statistically significant in the hypothesized direction, the significance faded once we included control variables. This likely resulted from either the small sample size, or, more likely, the lack of variation seen in only the top 20 MSAs. As a result, we expanded to include all MSAs with over 100,000 private employees.

Using the expanded sample we find that an increase in two standard deviations of σ (a recession with σ approximately three percentage points higher) would increase the maximum unemployment rate for that MSA by approximately 1.5 percentage points. A one standard deviation increase in high school graduation rates (going from 85% to 90%)

would mitigate approximately 0.37 percentage points of the increase in the unemployment rate. The results on unemployment rate are consistent with the hypothesis based on previous literature, but unemployment is not the only measure of recession.

In order to test the robustness of σ's effect on depth of recession, we replaced the maximum increase in the unemployment rate with the largest fall of the economic conditions index constructed by Arias *et al.* (2016) for the 66 largest MSAs. σ continued to have a significant effect in explaining variations in this measure of the depth of a recession. Assessing the policy implications and economic impact of these results, though, is more difficult as the left-hand side variable is constructed from a dynamic factor model, in which the weights of the inputs are unknown.

The biggest fear in regression analysis is always that there are other variables that influence the LHS variable, and by omitting these as control variables, the parameter of interest (here the coefficient on σ) is biased - this is the case of omitted variable bias. To control for other time-invariant MSA characteristics, a two-period panel regression was used. We were limited to two time periods due to limitations in data availability. The results show that, with the exception of the full model for only 20 observations, σ significantly impacts the depth of the recession. More specifically, areas that saw deeper recessions in 2008 also saw greater increases in churning, holding all else constant.

Lastly, I look into sigma's effect on the length of recession. I use the time for real GDP to recover as opposed to employment in order to more fully capture areas that may have recovered jobs, but have not retained the same quality of jobs held prior to the recession. Under this framework, σ is only a significant factor in the number of years for

GDP to recover until the addition of how far GDP fell is included. This measure suffers from MSAs that have yet to fully recover by considering the current year as the final year in the length to recover. In attempt to control for this, the ratio of current real per capita GDP was used as the LHS variable. This measure was not significant, which could potentially indicate that MSAs have been able to fully recover despite larger measures of σ.

There are several limitations of our analysis which future work will have to address. First, there have only been two national recessions since MSA-level GDP and employment data became available. Even national recessions are relatively infrequent, but at least we can make conclusions by observing more than two of these for the U.S. Drawing general conclusions from the results observed should therefore be taken with this caveat in mind. Although the 2001 recession did not see much movement in σ at the national level, we were able to use it here to control for factors across MSAs that are time-invariant. Our main results remained fairly robust in the difference-specification.

Another area that validates further investigation is the type of economic policy necessary at the MSA level to mitigate the effect of future σ effects (large changes in sectoral composition). Economists do not really have the ability to predict the future shocks that trigger a recession, be it locally or nationally. However, our results have shown that education has a mitigating effect on the depth of recession. Future research should focus more on specifically the type of education that is required to lower the devastation brought on by large sectoral changes.

Much of the motivation for this paper comes at a time when many have talked about the arrival of the 4th industrial revolution (AI, automation, etc.) The results of this paper do not directly assess the effect of automation, but there is potential for future research to interact areas that have faced large increases in dispersion of employment with areas that are vulnerable to automation. A gap would still remain in the policy implications, but perhaps it would paint a clearer picture as to areas most vulnerable to deeper recessions, which could then lead to preventative measures.

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