Interstate Labor Market Connectedness in the United States

by

Berkeren Büyükeren

A Dissertation Submitted to the
Graduate School of Social Sciences and Humanities
in Partial Fulfillment of the Requirements for
the Degree of

Master of Arts

in

Economics

KOÇ ÜNİVERSİTESİ

To my beloved family and my grandfather Mehmet Şeker, the first intellectual in my life

ABSTRACT

Interstate Labor Market Connectedness in the United States
Berkeren Büyükeren
Master of Arts in Economics

This paper investigates the labor market connectedness across the US states. We apply the Diebold-Yilmaz Connectedness Index (DYCI) methodology to weekly initial unemployment claims to obtain connectedness measures across 51 states between 1989 to 2021. The system-wide connectedness increases during the US recessions since 1990. We also show that changes in the monetary policy stance affects the regional unemployment levels and their connectedness across states. A significant section of the thesis is devoted to analyzing the state-level initial unemployment claims and their connectedness across states during the COVID-19 recession. We show that in addition to the number of new COVID-19 cases, state-level government policy stringency and community mobility patterns play a critical role in explaining the unemployment dynamics during the COVID-19 recession. The same factors defined in relative terms over the pairs of states as well as distance and the value of shipments across states also explain the transmission of unemployment shocks across states during the COVID-19 recession.

Keywords: Unemployment Insurance, Connectedness, COVID-19, Local labor markets, Regions, Business cycles, Vector autoregression, Variance decomposition.

ÖZETÇE

ABD'de Eyaletler Arası İş Piyasası Bağlılığı
Berkeren Büyükeren
Ekonomi, Yüksek Lisans

Bu çalışma ABD'de eyaletler arası emek piyasası bağlantılılığını incelemektedir. Bu amaçla Diebold-Yılmaz bağlantılılık endeksi yöntemi 51 eyaletin haftalık işsizlik sigortası başvurularına uygulanmıştır. 1990'dan günümüze ABD'deki resesyonlarda toplam bağlantılılık endeksi arttığı gözlenmiştir. Para politikası kararlarının eyalet düzeyinde işsizlik ve eyaletler arası işsizliğin bağlantılılığı üzerindeki güçlü etkisi de ayrıca gösterilmiştir. Çalışmanın önemli bir bölümü, COVID-19 resesyonu sürecinde eyalet düzeyinde işsizlik sigortası başvuruları ve onların eyalet arası bağlantılılığının analizine ayrılmıştır. Yeni COVID-19 vaka sayılarının yanı sıra, eyalet düzeyinde kamu sağlığı politikalarının ve topluluk hareketliliğinin COVID-19 resesyonu sırasında işsizlik dinamiklerini belirlemede önemli bir rolü olduğu gösterilmiştir. Bu değişkenlerin ikili eyaletler arasında göreli olarak tanımlanmış hallerinin yanı sıra eyaletler arası mesafe ve mal ticaretinin büyüklüğü de COVID-19 resesyonu boyunca işsizlik şoklarının eyaletler arası yayılmasını açıklamaktadır.

Anahtar Kelimeler: İşsizlik sigortası, Bağlanmışlık, COVID-19, Yerel İşgücü Piyasaları, İş Döngüleri, Vektör otoregresyon, Varyans ayrıştırması.

ACKNOWLEDGMENTS

I am indebted to my supervisor Prof. Kamil Yılmaz for the academic help and guidance. I would also like to thank Prof. Cem Çakmaklı and Prof. Erol Taymaz for being members of my thesis committee and spending their valuable time. I thank Cem Özdemir, Emre Can Oral and Taylan Alpkaya for their moral support and comments.

TABLE OF CONTENTS

List of Tables viii

List of Figures ix

Chapter 1: Introduction 1

Chapter 2: Literature Review 4

2.1 Characteristics of Regional Labor Markets 4

2.2 Recent Methodologies on Labor Market Interdependencies 5

2.3 Labor Markets during COVID-19 Crisis 7

Chapter 3: Data 9

Chapter 4: Methodology 11

4.1 Diebold-Yilmaz connectedness measures 12

4.1.1 Pairwise directional connectedness 12

4.1.2 Aggregate directional connectedness 13

4.2 Estimation 14

4.3 Estimation of high-dimensional VARs 14

4.3.1 Graphical Display of High-Dimensional Variance Decompositions . . 15

Chapter 5: Overview of the last three decades of the U.S. labor markets 17

5.1 1980s and the Road to Globalization 19

5.2 The Roaring Nineties: Belle Époque in the global economy 20

5.3 2000-2007: The Inert pre-Great Recession 21

5.4 The Great Recession 21

5.5 The Recovery: Post-Great Recession 22

5.6 The Great Recession 2.0: The COVID-19 pandemic 23

Chapter 6: Network Estimation Results **25**

6.0.1 Dynamic Estimation of Interstate Labor Market Network: System-Wide Connectedness 25

6.0.2 Dynamic Estimation of Interstate Labor Market Network: Interregional (Conditional/Pairwise) Connectedness 35

Chapter 7: Network Structure of Unemployment Connectedness on Various Periods **42**

7.1 1990s 42

7.2 2000s,2010s and 2020s 44

Chapter 8: Labor Markets and State-Level Government and Community Responses **48**

8.1 Pairwise Connectedness and Panel Secondary Regressions 51

LIST OF TABLES

8.1 Panel Regressions, Initial Claims on CMI and GSI 50

8.2 Secondary Panel Regressions (March 21, 2020 - May 1, 2021) 54

LIST OF FIGURES

6.1 System-wide Connectedness of State-Level Initial Unemployment Claims . . 25
6.2 System-wide Connectedness of State-Level Initial Unemployment Claims with Unemployment Rates 26
6.3 System-wide Connectedness of State-Level Initial Unemployment Claims with Important Events 30
6.4 System-wide Connectedness of State-Level Initial Unemployment Claims with Federal Funds Rate 32
6.5 Net Connectedness between Northeast and All Other States 36
6.6 Net Connectedness between South and West and Midwest 38
6.7 Net Connectedness between Midwest and West 40

7.1 Network Graph for Unemployment Connectedness, 03.02.1990 43
7.2 CNetwork Graph for Unemployment Connectedness, 03.02.1990 43
7.3 Network Graph for Unemployment Connectedness, 14.10.1995 44
7.4 Network Graph for Unemployment Connectedness, 16.02.2002 45
7.5 Network Graph for Unemployment Connectedness, 09.05.2008 45
7.6 Network Graph for Unemployment Connectedness, 14.03.2009 46
7.7 Network Graph for Unemployment Connectedness, 14.10.2017 46
7.8 Network Graph for Unemployment Connectedness, 27.02.2021 47

Chapter 1

INTRODUCTION

In the U.S. economy, the number of unemployment insurance claims has been one of the important leading indicators of the business cycle. The weekly availability of this data helps policymakers correctly gauge the state of the overall economy and identify those regions/states that are lagging or leading the performance of the overall economy. Additionally, with the outbreak of the COVID-19 pandemic over a year ago, an unprecedented event of the 21st century, the number of applications has reached an all-time high in the U.S., which attracted many economists' attention. To that end, we apply the Diebold and Yilmaz (2014) framework to understand further the underlying network structure of the U.S. labor markets.

We firstly give a brief overview of the last three decades in the American local labor markets. We then conduct connectedness analysis on the 51 states and discuss the implications of the system-wide connectedness. Furthermore, we compute the interregional connectedness by aggregating the regions by their respective dummies. Thereafter, we proceed with the analysis of the respective network structure of unemployment on important dates. This allows us to capture the dynamic structure of unemployment connectedness in a more detailed fashion.

The second part of the paper focuses on the recent COVID-19 pandemic, which we investigate separately from the system-wide connectedness analysis. While COVID-19 had become a significant health threat worldwide, its direct impact on the economy and employment, which effectively prevents sick employees from going to work, is less critical. Its largest impact in the labor market stems from the fact that it is a contagious disease among humans, which can be prevented only through social distancing and sometimes closure of public spaces. We are interested in understanding how the COVID-19 pandemic affected the regional unemployment dynamics and the potential spillovers of unemployment across the U.S. states. To this end, we use the Diebold-Yilmaz connectedness index (Diebold and Yilmaz (2014)) framework to analyze how unemployment shocks spilled over across the U.S. states during the pandemic.

The Diebold-Yilmaz framework relies on the forecast error variance decomposition from a Vector Autoregression (VAR) model to obtain an estimate of the underlying network. To measure the strength of the directed edge from the state (in our case, the unemployment spillover of the respective state) i to state j, the model tries to explain the following: "What percent of the forecast error variance of unemployment change of state j is due to shocks to the unemployment change of state i?".

Although more real-time data is available today than before, initial unemployment claims data still presents crucial information about the economy's structural dynamics. One can delineate a multifaceted analysis of U.S. labor markets by enriching the U.I. or I.C. data with different information. Preceding studies, such as Farber (2011) and Elsby et al. (2010), compare the differences in the labor market dynamics within previous crises. On the other hand, Dube and Lindner (2021) and Fishback and Seltzer (2021) investigate the effects of local spillovers on the regional minimum wages. There has been no study that combines state characteristics and their respective labor market connectedness from a time-series perspective to the best of our knowledge. Applying the connectedness analysis to regional labor markets, we offer a more comprehensive approach that uses the multivariate time series techniques to approximate the labor market linkages across the states.

Our research extends the literature in two ways: estimating the interstate labor market networks and their determinants (only for the COVID-19 pandemic period). The interstate labor markets have never been studied before from a network perspective, and it presents many different implications. A time-series approach to the unemployment rates shows how other states or regions react to shocks. By observing the interstate labor markets' network structure, we delineate which states are particularly influential in the unemployment spillovers. For the latter part of our paper on the pandemic period, we search for the determinants of the pairwise labor market connectedness by embedding information on state characteristics and linkages between pairs of states into the secondary regressions. More precisely, this paper answers the following question: From a network theory perspective, how do the state labor markets react to different shocks, and how do the resulting changes in the initial unemployment claims spill over to other states?

Additionally, this article utilizes LASSO techniques to overcome the dimensionality problem, which results from the large number of states considered in the connectedness analysis (see Demirer et al. (2018)). We include time-series data on initial unemployment claims in each of the 50 states (plus Washington, D.C.) in our analysis, not a 'representative' state from each U.S. region. We capture the dynamic structure of the interstate unemployment spillovers across 51 states by estimating Vector Auto Regression (VAR) of initial unemployment claims over the rolling sample windows. Using the resulting variance decomposition matrices, we obtain granular and aggregate connectedness measures. Rolling the sample window over time allows us to obtain the connectedness measures over time.

The remainder of the study is organized as follows. Section 2 presents the literature on labor market connectedness from different countries and previous methods employed to explain the unemployment spillovers. Section 3 describes the dataset. Section 4 describes the methodology. Section 5 presents a brief history of the last three decades of the U.S. local labor markets. Section 6 presents the full sample estimation results of system-wide and intra and interregional connectedness. Section 7 presents the network structure and its changes on crucial dates for the labor markets. Section 8 justifies the secondary panel regression analysis by conducting primary fixed-effect panel regressions. The penultimate section, Section 9, consists of the secondary fixed-effect panel regressions that explain the determinants of labor market connectedness. Section 10 concludes the paper.

Chapter 2

LITERATURE REVIEW

2.1 Characteristics of Regional Labor Markets

Regional unemployment can be addressed from both microeconomic and macroeconomic perspectives. In that regard, we are most interested in the macro labor framework approach to the subject, in which the geographical proximity is larger. Several studies explain the labor market heterogeneities and embed these heterogeneities into standard search and matching models. Barnichon and Figura (2015) discuss that standard matching function does not take labor market heterogeneity into account and only cooperates with the *labor market tightness*. Therefore, they introduce dispersion and composition effects to the standard matching function and name it as "generalized matching function." Rappaport (2012) investigates the persistent differences in unemployment across metro areas and states that workforce skills are essential for explaining the persistent and substantial differences in metro unemployment. Additionally, the metro areas' intrinsic characteristics, such as metro weather, metros' proximity to the ocean and Great Lakes coasts and hilliness, are also considered essential in understanding long-term unemployment differences. David and Dorn (2013) analyze the polarization trend in the United States by focusing on the service sector. They find that local labor markets with a higher majority of low-skill service jobs have substantially higher job polarization. Kline and Moretti (2013) offer place-based policies to the heterogeneity on spatial unemployment. Di Caro (2015) shows that the transient, engineering in that case, and permanent, geography, have been influential in the heterogeneous resilience of the regional Italian labor markets.

A relatively more popular research topic is regarding the different responses to a particular nationwide (or global) crisis at a given point in time. Another alternative follows from a time-varying structure, in which the effects of different crises are analyzed. Yashiv (2007) presents some of the primary business cycle facts and labor market dynamics from a more generalized perspective. The Global Financial Crisis of 2008 naturally influenced the macro labor research extensively, and there were some differences in terms of its effects on the labor market outcomes compared to the previous crises. Farber (2011) addresses such differences from a time series perspective, comparing various crises from 1984 to 2010, and found out that the Great Recession has been particularly harmful because of its persistent unemployment effects. Şahin et al. (2014) try to explain the persistent unemployment by the mismatch phenomena entrenched in the labor markets after the Global Financial Crisis. On the other hand, Dao et al. (2017) observe how labor mobility behaves during aggregate economic downfalls. According to their analysis, labor market connectedness should increase during recessions as a response to the interstate migration due to regional asymmetries in job opportunities increases in recessions.

2.2 Recent Methodologies on Labor Market Interdependencies

Although no studies explicitly take the labor market connectedness with a time-varying structure into account, some studies try to measure the labor market dependencies in a spatial setup. Burda and Profit (1996) integrate the regional mobility into a matching function to investigate the spatial spillovers in the Czech Republic's local labor markets. Hynninen (2005) utilizes a matching approach to study the spillover effects in Finnish labor markets from a spatial perspective. She finds that there is a congestion effect in Finnish local labor markets. Additionally, spatial spillovers across local labor markets exacerbate the congestion effect. Manning and Petrongolo (2017) stress out the possible inefficiencies of place-based unemployment policies by referring to the local spillovers. They build their analysis upon the baseline search model and create a structural model that allows them to do policy evaluation by theoretical predictions. Also, under a spatial setup, Lottmann (2012) measures the spatial dependencies in German labor markets by a spatial weight matrix. Following Lottmann (2012), Higashi (2018) also employs a spatial weight matrix and finds that there are significant inter-regional spillovers in job matching in Japan. Higashi (2018) further states that the Great East Japan Earthquake of March 2011 had substantially increased the spatial spillovers in job matching. Such a catastrophic event in a specific region had major implications for the local labor markets; therefore, it is crucial to understand how the pandemic affects the local labor markets.

As Barnichon and Figura (2015), several papers expand the conventional matching function through their analysis. For example, Fahr and Sunde (2006) alter the standard matching function to understand if the regional disparities in employment conditions are the main drivers of regional mobility patterns. To that end, they disaggregate the dependent variable, job searchers, into two different categories, namely unemployed job seekers and employed job seekers. Additionally, they further extend the disaggregation to another dimension, namely local vs. non-local job searchers. Their results conclude that both dimensions are vital to understanding regional mobility, and such disaggregation is essential to have a more insightful interpretation of the labor market dependencies.

Another recent study investigating the relationship between local labor market disparities and job-matching efficiency with the standard matching function is Fedorets et al. (2019). Like Fahr and Sunde (2006), they do disaggregate the job searchers and the labor markets to regional and occupational labor markets. Their results end up with positive regional spillover effects of unemployment and vacancies and a negative occupational spillover for unemployment (for the people who are in similar occupations).

From a business cycle synchronization (for the regional level) framework, Hamilton and Owyang (2012) investigate the regional business cycles and differences in their respective timing of business cycles. By analyzing the Markov-switching components of a panel data set - containing time series and cross-section data- they find there is indeed a business cycle synchronization across states. The main heterogeneity in the business cycle synchronization is in the timing dimension of the recessions. The heterogeneity in facing and recovering from a recession differs across state-level labor markets in the U.S. Hamilton and Owyang (2012) further argue that the only exceptions are the states which are dominant in agriculture and energy, which do have different recession than the other remaining labor markets. On the other hand, Caliendo et al. (2018) analyze the impact of the regional and sectoral productivity changes from a more granular point of view. The pairwise trade flows and the interstate trade relations are central in their analysis. Their findings suggest that the shocks in productivity lead to aggregate change in the U.S. economy. In the COVID part of the paper, we follow a similar approach to Caliendo et al. (2018) in understanding the effect of trade flows and geographical factors like distance to understand the pairwise connectedness across states.

Our study is mainly influenced by the above given two articles, Fahr and Sunde (2006) and Fedorets et al. (2019). The multifaceted aspect of those studies raises many different questions for our research, and they are directly related to the labor market spillover effects that we measure. Yet, they are built on a spatial framework, which cannot be used to study the effects of the COVID-19 pandemic. This study attempts to overcome the constraint imposed by the short sample period of analysis and further expand the investigation to bring out a larger scheme of how local labor markets work.

Ultimately, Bailey et al. (2018) is an analogous study for our research as it measures interstate social connectedness. Like that study, we also use within-US trade flows extensively as an explanatory variable for labor market connectedness by employing the Commodity Flow Survey data, which we explain in detail in the following section.

2.3 Labor Markets during COVID-19 Crisis

This subsection presents the new literature raised during the COVID-19 pandemic due to its groundbreaking effects throughout the world. The U.S. has been one of the most seriously affected countries by the crisis that the epidemic created, which is now conventionally considered both demand and supply shock to the whole economy.

Several studies explain the heterogeneity in the U.S. labor markets during COVID-19. Montenovo et al. (2020) present an analysis comparing employment disruptions of 2001, 2008 and the current crisis by distinguishing particular groups, genders, etc., who were significantly affected. Their regression analysis includes job characteristics in various ways, such as work-from-home availability, essential work designations, worker level COVID-19 risk, human capital, and family structure. Another contribution, which has influenced our work, Dingel and Neiman (2020) characterizes telework opportunities for different states and counties. By such characterization, a more nuanced view on the mitigation effects of the *tele-workability* is presented.

Apart from the articles mentioned above, we are also interested in understanding the effects of major policy decisions on the labor market outcomes. Gupta et al. (2020) present evidence on the impacts of social distancing policies on labor market outcomes. On the other hand, Akovali and Yilmaz (2020) explain the effects of public health policy on state-level COVID-19 rates, which affects labor market outcomes. By using April 2020 CPS data, Fairlie et al. (2020) specifically focus on the pandemic's impacts on the unemployment of minorities. They concluded that black unemployment was significantly more affected than white unemployment, yet less than the difference in the Great Financial Crisis of 2008. Amburgey and Birinci (2020) find that the workers in occupations with lower average earnings had been affected disproportionately from the pandemic. Amburgey and Birinci (2020) state that occupations that belong to the bottom quintile accounted for 34 percent of the total increase in unemployment in the U.S. Birinci et al. (2020) integrate the standard epidemiological model of Kermack and McKendrick (1927) into an equilibrium search model for comparing different labor market policies during the pandemic, namely U.I. expansions and payroll subsidies. Birinci et al. (2020) finds that these two labor market policies complement each other, and the optimal allocation consists of 20 percent of the budget to the payroll subsidies and 80 percent of the budget to the U.I. expansion. In another contribution, Mitman and Rabinovich (2020) find an optimal policy for U.I. benefits by focusing on the amount and timing of the unemployment benefits. Ganong et al. (2020) employs microdata on earnings to analyze the effects of the additional $600 weekly benefit, namely the Federal Pandemic Unemployment Compensation (FPUC). The study indicates that the FPUC supplement has been one of the main determinants of the overall income dynamics at the pandemic's primary stages, as it altered the sectoral income levels majorly. Marinescu et al. (2020) argue that the potential moral hazard problems associated with the FPUC supplement have not been significant, implying that the FPUC supplement did not offset the total increase in applications per job. On the other hand, Kahn et al. (2020) document the general downfall in vacancy postings and surge in U.I. claims. Kahn et al. (2020) argue that the damage in the economy was not solely due to stay-at-home orders. The damage would not be eliminated directly by removing the public policy restrictions associated with the pandemic. Coibion et al. (2020) state various facts on the unusual nature of the COVID-19 crisis. In addition to this, Cajner et al. (2020) take a snapshot of the U.S. Labor Market from a monthly time-varying perspective. Both of these studies help in understanding the economic consequences of the pandemic in its early stages. Hedin et al. (2020) present various data and associated results derived by the California Policy Lab regarding the eligible population who enjoyed the U.I. benefits during the pandemic. Ultimately, Goolsbee and Syverson (2020) investigate how much the economic downfall was caused by public policy versus community response. The main interest of Goolsbee and Syverson (2020) is directly related to our study since we try to understand the determinants of the interstate labor market connectedness using panel data regressions.

Chapter 3

DATA

Our study estimates the interstate labor market connectedness by using the Initial Claims data. Although the dataset has an evident lag compared to a real-time setup, it offers sufficient ground to conduct this study with a time-series perspective. After performing the connectedness analysis on the state-level labor markets, we aim to explain the determinants of labor market spillovers across states employing secondary regressions. To illustrate the causal relationship, we use different sets of data along with the initial claims data. In this section, we briefly describe the data used in the analysis.

As explained by the St. Louis FED, an UIC is filed by an unemployed individual after a separation from an employer. The claim requests a determination of the unemployment insurance program's basic eligibility requirements. It is weekly state-level data collected since 1970. Having a state-level data set spanning 50 years, one can conduct extensive research on the evolution of U.S. interstate labor market dynamics. Additionally, this also allows researchers to compare how different economic, political, and financial shocks impacted labor markets in various states.

The study employs different datasets to understand better the causal relationship between interstate labor market connectedness and its determinants within the secondary regressions. The primary data that we utilize is the Commodity Flow Survey (CFS), where we employ the data from 2017, which is the latest year of the dataset. Commodity Flow Survey is an extensive dataset presented every five years by Census Bureau. Our study relies on the CFS data to capture the underlying domestic trade linkages between states. In particular, we conjecture that there is a relationship between labor market connectedness across states and interstate domestic trade flows. We also use the geodesic distance between pairs of states as an RHS variable in pairwise connectedness regressions to check for the possible adverse impact of distance on unemployment spillovers across states.

In terms of the pandemic part of our study, as Akovali and Yilmaz (2020), we use the government policy stringency index (GSI) to measure the government response to the pandemic, which is developed by a group of researchers at the Blavatnik School of Government, University of Oxford. Additionally, to understand how the state governments' and communities' response to pandemic affected the nationwide and regional economic and social activity, we use the Google Community Mobility Indicators dataset. Johns Hopkins University Center for Systems Science and Engineering provides the daily number of confirmed new cases of COVID-19.

Throughout our study, we will focus on a sample of 51 states. We will explicitly inform the reader when using a smaller sample for the network estimations and secondary regressions.

Chapter 4

METHODOLOGY

There are various channels through which a state's labor market shock can affect another. Determining the key variables of interest through which these shocks are transmitted is not an easy task. There are no current studies available on the labor market spillovers within a time-series perspective to the best of our knowledge. This section provides a concise overview of the empirical approach used to obtain estimates of the U.S. interstate labor market network.

Our analysis of the interstate labor market spillovers will be built on the Diebold-Yilmaz connectedness index (DYCI) approach. The DYCI methodology makes heavy use of the variance decompositions of estimated VAR models. It has been developed in several papers, namely, Diebold and Yilmaz (2009), Diebold and Yilmaz (2012), Diebold and Yilmaz (2014), and extended to large VARS in Demirer et al. (2018).

In our empirical analysis, we follow the DYCI framework for several reasons. The first reason is directly related to its intuitive nature. The pairwise connectedness from state j to state i provides a measure of what percentage of variation in unemployment of state i is due to the shocks that affected state j's labor market. Second, we can estimate VAR models and obtain connectedness measures in rolling sample windows to allow for changes in connectedness measures over time. Third, the estimated connectedness measures correspond to the estimated weighted edges across state labor markets, which directly maps into the network theory. Our final reason for using the DYCI methodology is its flexibility to estimate high-dimensional data. By employing LASSO estimation, we can estimate high dimensional VAR and obtain the connectedness measures.

Within the remaining part of this chapter, we will present the Diebold Yilmaz Connectedness Measures (as in Diebold and Yilmaz (2014)) and the LASSO estimation of the VAR Model to overcome the dimensionality problem.

4.1 Diebold-Yilmaz connectedness measures

The Diebold-Yilmaz Connectedness Index (DYCI) method provides a network estimate by relating forecast error variance decompositions from VARs to edge weights within networks. The way that the variance decomposition matrix yields a measure of edge weights is intuitive; it shows the percentage of unemployment variation in state i due to the labor market shocks in state j. The variance decomposition is based on an N-variable VAR(p) model, $x_t = \sum_{i=1}^{p} \phi_i x_{t-i} + \epsilon_t$ where $\epsilon \sim (0, \sum)$. The moving average representation is $x_t = \sum_{i=1}^{\infty} A_i \epsilon_{t-i}$ where $A_i = \phi_1 A_{i-1} + \phi_2 A_{i-2} + ... +$, A_0 being an NxN identity matrix and $A_i = 0$ for $i < 0$.

One of our methodology's main advantages is that it overcomes the identification problems associated with high-dimensional setups such as this study. Diebold and Yilmaz (2014) framework, which is invariant to the ordering of variables, is adopted to gather the connectedness measures while using the 'generalized variance decomposition' of Koop et al. (1996).

Another problem of high dimensionality in VAR model estimation is that the number of parameters to be estimated increases quadratically. We use Demirer et al. (2018) approach of estimating sparse VAR of unemployment volatilities by enjoying the LASSO estimator.

4.1.1 Pairwise directional connectedness

State j's contribution to variable i's H-step-ahead generalized forecast error variance,

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \sum e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h \sum e_i)}, H = 1, 2, ... \tag{4.1}$$

where $\sum$ is the covariance matrix for the disturbance vector ϵ, σ_{jj} is the standard deviation of the disturbance for the jth equation, A_h is the h-step moving average coefficient matrix, and e_i is the selection vector with one as the ith element and zeros otherwise.

Since we follow Koop et al Generalized VAR Framework, the shares of variance need not necessarily add up to 1, which is generally as: $\sum_{j=i}^{N} \theta_{ij}^{g}(H) \neq 1$. Thus, following Diebold and Yilmaz (2014) framework, each entry of the generalized variance decomposition matrix are divided with the sum of the entries of their respective rows for normalization. We obtain the following:

$$\tilde{\theta}^g_{ij}(H) = \frac{\theta^g_{ij}(H)}{\sum_{j=1}^{N} \theta^g_{ij}(H)}. \quad (4.2)$$

By construction, $\sum_{j=1}^{N} \tilde{\theta}^g_i j(H) = 1$ and $\sum_{i,j=1}^{N} \tilde{\theta}^g_{ij}(H) = N$. $\tilde{\theta}^g_{ij}(H)$ denotes the directional pairwise connectedness from state j to state i. Connectedness is generated by state j to state i if $\tilde{\theta}^g_{ij}(H)$ is positive. In the terminology of network theory, $\tilde{\theta}^g_{ij}(H)$ is the estimated size of the edge from node j to node i.

4.1.2 Aggregate directional connectedness

Another observation can be made on the connectedness measures on more aggregate measures after deriving the pairwise connectedness measure between state i and j. For instance, one can examine the total directional connectedness from state i to all remaining states and the total directional connectedness to state i from all remaining states. As Diebold and Yilmaz (2014), our study will refer to these as 'to connectedness' and 'from connectedness' of state i, respectively.

The total directional connectedness to state i from all other states j is as follows:

$$C^H_{i\leftarrow\cdot} = \frac{\sum_{j=1,j\neq i}^{N} \tilde{\theta}^g_{ij}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}^g_{ij}(H)} x100 = \frac{\sum_{j=1,j\neq i}^{N} \tilde{\theta}^g_{ij}(H)}{N} x100. \quad (4.3)$$

Analogously,the total directional connectedness from state i to all other states j is as follows:

$$C^H_{\cdot\leftarrow i} = \frac{\sum_{j=1,j\neq i}^{N} \tilde{\theta}^g_{ji}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}^g_{ji}(H)} x100 = \frac{\sum_{j=1,j\neq i}^{N} \tilde{\theta}^g_{ji}(H)}{N} x100. \quad (4.4)$$

Ultimately, the system-wide connectedness can be obtained as follows:

$$C(H) = \frac{\sum_{i,j=1,i\neq j}^{N} \tilde{\theta}^g_{ij}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}^g_{ij}(H)} = \frac{\sum_{i,j=1,i\neq j}^{N} \tilde{\theta}^g_{ij}(H)}{N}. \quad (4.5)$$

The above-given measure is called *system-wide* connectedness, and it is merely the average of total directional connectedness measures across states.

4.2 Estimation

So far in this section, we have introduced the building blocks of the DYCI methodology. In the rest of the section, we will discuss the implementation of the methodology in the context of the U.S. interstate labor markets.

4.3 Estimation of high-dimensional VARs

As we have already discussed above, using data for 51 states in our connectedness analysis, we are facing the high dimensionality problem. We will follow Demirer et al. (2018) to overcome the high dimensionality problem. To recover degrees of freedom, one can use pure shrinkage methods (such as traditional informative-prior Bayesian analyses or ridge regression) or pure selection methods (such as the Akaike information criterion and Schwartz information criterion). Yet, methods combining shrinkage and selection is more appealing for our analysis.

In this section, we will briefly explain LASSO. Consider the below-given least-squares estimation:

$$\hat{\beta} = arg_{\beta}min \sum_{t=1}^{T}(y_t - \sum_{i} \beta_i x_{it})^2, \tag{4.6}$$

subject to the constraint below:

$$\sum_{i=1}^{K} |\beta_i|^q \leq c. \tag{4.7}$$

Or, equivalently, consider the below-given penalized estimation problem:

$$\hat{\beta} = arg_{\beta}min \left[\sum_{t=1}^{T}(y_t - \sum_{i} \beta_i x_{it})^2 + \lambda \sum_{i=1}^{K} |\beta_i|^q \right]. \tag{4.8}$$

Concave penalty functions, which are non-differentiable at the origin, produce selection and smooth convex penalties (such as q=2, the ridge regression estimator) produce shrinkage. Thus, penalized estimation nests and combines selection and shrinkage.

LASSO (Least Absolute Shrinkage and Selection Operator) has been introduced by Tibshirani (1996), and it solves the penalized regression problem for $q = 1$. Therefore, it selects and shrinks. Additionally, the LASSO requires only one minimization, in which it employs the smallest q that makes the minimization problem convex. We will further refine the estimation method by using the elastic net estimation. Elastic net estimation linearly combines the penalties of the LASSO and the ridge methods.

4.3.1 Graphical Display of High-Dimensional Variance Decompositions

In the graphical analysis, one can, in principle, present all nodes and edges. However, in such a case, with its 51 nodes and 2551 edges, it would be impossible to distinguish between strong vs. weak edges. For that reason, we show only the thickest edges in the network graphs. However, this is solely for visual purposes; in the secondary regressions, we use data on all 2551 edges in our analysis.

We the open-source Gephi software (https://gephi.org/) to create all network graphs. We use node size, node color, edge thickness, edge arrow size, edge color, and node locations to reveal further information regarding the graph.

Node Size Indicates the Total Non-Farm Employment

The annual averages of the Non-Farm Employment throughout the full sample determine the node sizes. A state with a higher NFE in the full sample period has a bigger node.

Node Color Indicates Total Directional Connectedness "To Others"

The presented node colors indicate total directional connectedness to other states, which ranges from 3DFA02 (bright green, the weakest), to ED6DF22 (luminous, vivid yellow), to CF9C5B (whiskey sour), to FC1C0D (bright red), to B81113(dark red, the strongest). The color range is shown in more detail in Figure 1. This means that a state with less influence on the total directional connectedness "to others" will have a color closer to bright green, while a state with more influence will have a color closer to dark red, respectively.

Node Location Indicates Strength of Average Pairwise Directional Connectedness

Node locations are determined using the ForceAtlas2 algorithm of Jacomy et al. (2014) as implemented in Gephi. The nodes repel each other, yet the edges attract the nodes they connect in the ForceAtlas2 algorithm. The algorithm finds a steady state in which repelling and attracting forces balance one another, determined by the average pairwise directional connectedness 'to' and 'from' for every pair of nodes. The node locations at the steady-state do depend on the initial node locations and, therefore, not unique. This is not a matter of interest for us; we are interested in relative node locations in the equilibrium rather than absolute node locations.

Link Arrow Size Indicates Directional Connectedness "To" and "From"

The size of the arrow of the edge from node i to node j increases with the pairwise directional connectedness from node i to node j.

Chapter 5

OVERVIEW OF THE LAST THREE DECADES OF THE U.S. LABOR MARKETS

In this section, the last thirty years of the U.S. labor markets and their major developments will be discussed. As Holzer and Hlavac (2012) state, the three decades have been quite uneven. This, in turn, requires a brief overview of the broad facts concerning the U.S. labor markets before we go through the connectedness analysis.

One common thing between all the three periods has been the heterogeneity of gains and losses. Different educational groups and sectors have faced different developments, and job polarization has increased more and more. One of the most striking developments for the labor markets has been automation and what it brings along. Studies such as Autor et al. (1998, 2008, 2010) discuss the skill-biased technological change and the shift in the demand from routine to non-routine service sector jobs. We believe that this trend is influential in the local labor market connectedness in the U.S. On the other hand, as Holzer and Hlavac (2012) indicate, there hasn't been a dramatic decline in middle-skill jobs in the last three decades. Their study suggests that the middle-skill jobs decreased 10 percent from 1979 to 2007, 59 to 49 percent.

The differences in the evolution of labor markets across regions are worth discussing. In 1979, almost all regions had similar mean hourly wages, ranging from 15.43 (South) to 17.96 (West). In 2007, the mean hourly wages ranged from 20.42 (South) to 23.57 (Northeast). The unemployment rate in 2007 has been relatively more even, ranging from 4.19 percent in the South to 5.12 percent in Midwest. West leads the average unemployment in 2007-2010 with 6.17, with the last being Midwest with 4.49 percent. Additionally, as Holzer and Hlavac (2012) suggest, the workers in Midwest have been affected more from the crises than the remaining labor force in the other regions of the U.S. This is an interesting finding, as it shows that Midwestern workers became the most disadvantaged workers in terms of regions. The mean wage of a Midwestern worker was one of the highest in 1979, yet in 2007 it became almost the lowest.

In that regard, the area known as 'Rust Belt' represents a considerable difference compared to the rest of the local labor markets in the U.S. Alder et al. (2014) investigate the determinants of the general economic downfall in the region. Rust Belt cities had the highest growth rates, populations and productivity in 1950-1980. The labor market dynamics of the cities reversed after 1980 as a consequence of the fall in manufacturing jobs. Alder et al. (2014) also argue that the fall is associated with the lack of strong labor union agreements. It is also documented that the dominant sectors in the Rust Belt region usually suffer from mistrust within firms and labor unions.

Although stated above, it is essential to note that demographics play a significant role in determining the labor market outcomes. The effects of the crises were a lot more pronounced on the black male labor force, unlike the white male educated labor force. Holzer and Hlavac (2012) state that the wage gains of the black and Hispanic labor force are relatively slow compared to other groups and with a lag. Additionally, from a more generalized point of view, Katz and Murphy (1992) show that the low-skill labor force has been consistently faced more pronounced adverse effects with respect to the nationwide shocks.

The regional income convergence is also a highly debated topic in labor economics. The per-capita incomes in the U.S. have been converging for more than a century, yet the convergence rate declined substantially over the last three decades. Ganong and Shoag (2017) approach this issue from an urban economics perspective, in which they introduce a panel instrument regarding housing supply. As a related topic, the minimum wages in the U.S. have always been a hot topic in labor economics. Derenoncourt and Montialoux (2021) is the first study where they investigate the effect of minimum wages on the disparities resulting from race. There are also studies regarding the city minimum wages and their impact on employment, such as Dube and Lindner (2021).

Political aspects of the labor market dynamics have been discussed extensively by researchers. Dorn et al. (2020) and David et al. (2013) discuss these political outcomes of globalization in the local labor markets of the U.S. Their findings suggest that the workers who have faced more severe consequences of import competition leaned more towards conservative parties. Other similar studies include Malgouyres (2017) (from France), Dippel et al. (2015) (from Germany), (the U.K. regarding Brexit votes) and Choi et al. (2020) present evidence from the U.S. labor force's political shift towards more conservative parties with respect to the NAFTA's effects on local labor markets. In their study, they first focus on counties that have been worst affected by NAFTA trade deals. They further show that those areas shifted from Democratic to Republican or became more supportive of the Republican Party. Furthermore, they document that after 1992 it is the common trend in the U.S. regardless of where workers reside. The labor force that supports protectionist policies shifted to the Republican Party.

In the remaining subsections, we briefly go through what happened in each of the three decades. We further divide the three decades into six: the 1980s, the pre-Great Recession, the Great Recession, the post-Great Recession, respectively. Before continuing any further, the reader should be aware that this section only briefly introduces some of the important events and developments in the U.S. labor markets. There are many other peripheral developments that we might have skipped.

5.1 1980s and the Road to Globalization

In the early years of the 1980s, there has been a global recession which was considered the second biggest recession after the Second World War. One of the primary drivers of the global recession was the energy crisis in 1979, which is mainly related to the Iranian Revolution. However, when thinking throughout the 1980s in the U.S., the biggest role of the downfall in the labor markets is due to Paul Volcker. Today, there is a period known as Volcker Era and it is known as a notorious period with high interest rates and unemployment. We will briefly discuss the major developments of that era below.

Paul Volcker, the 12th Chair of the Federal Reserve, has been an influential figure in determining the fate of the modern American economy. Well known Volcker Rule was a part of the reform period, under the Dodd-Frank Act, of the U.S. financial system. A recession also occurred during his term as FED Chair, widely known as Volcker Recession. Prior to Volcker's appointment, there were problems related to high inflation and an overheated economy. Although, as planned, the CPI had fallen tremendously with hawkish policies, these strict monetary policy decisions led to recessions in the early 1980s. During that period, the most pronounced effects were regarding unemployment and inequality. To give a brief measure of the hawkish policies, the interest rate of 11 percent in 1979 has almost doubled in two years with Volcker's policies. Today, the period is considered as the kickstart of the recent inequality trend in the U.S. and the further concentration of wealth in the 1 percent. From a macro perspective, Reagan and Volcker tried to decrease the penetration of government into the economy. The duo attempted to shift the economic power from the government to the markets and capital owners.

The end of full employment phenomena also corresponds to that period. Before the 1980s, the labor markets in the U.S. were quite tight and the economy was blossoming for the American labor force. After that time, the U.S. never experienced full employment phenomena until the 1990s. The natural level of employment in the U.S. has always been a highly debated issue. It constantly changes during unexpectedly high/low productivity periods. Yet, Hall and Kudlyak (2020) investigate the success of the U.S. business cycle successfully restoring itself to full employment after all the recessions that occurred in the last 70 years.

5.2 The Roaring Nineties: Belle Époque in the global economy

The U.S. labor markets experienced a considerable upward trend throughout the '90s, which is referred to as " *The Roaring Nineties*", a term coined by Krueger and Solow (2002). The nineties were also the peak years for globalization, and the productivity in the U.S. was soaring. As a result, there were substantial gains in employment. For instance, as Acemoglu et al. (2016) indicate, the employment-to-population ratio increased by more than 3 percentage points for women and 1.5 percentage points for men. Additionally, in 2000, the unemployment rate became 4 percent, which is the lowest since 1969. The employer demand (associated with very high consumer demand) was very effective in the low unemployment rates throughout that period. Also, the public and economic policy, such as Earned Income Tax Credit expansion, under Bill Clinton's administration boosted the labor force participation significantly.

In the financial sector, Glass-Steagall Act has been eased in implementation and Wall Street enjoyed the benefits after the appointment of Robert Rubin to the Treasury Department in 1995. During that decade, it is safe to say that the financial sector in the U.S. was one the biggest winners and their benefits were disproportionate compared to the Main Street. On a long-read at the Atlantic magazine, Joseph Stiglitz states some of the tyrannical behavior of the financial markets during that time. Those events include a multi-billion tax break for the U.S. exporters during that time, the debate on the privatization of nuclear power and the bailout of Long-Term Capital Management. On the other hand, Stiglitz also refers to East Asia's capitalist structure as problematic and consequently drivers of the 1997 Asian Financial Crisis.

5.3 2000-2007: The Inert pre-Great Recession

In the period between 2000 to 2007, called as pre Great Recession by some researchers, failed to generate such labor market outcomes. In the words of Holzer and Hlavac (2012), the growth during 2000-2007 has been very modest. There are many different factors behind it, and we will briefly go through the recent history.

One of the most important developments for the local labor markets' inertia is the import competition introduced by China. China has gone through many economic changes under Deng Xiaoping's reforms, which led to the country's accession to WTO in 2001. In that regard, David et al. (2013) and Acemoglu et al. (2016) capture the effects of this trade shock on the local labor markets in the U.S. Although globalization and trade with China bring several gains at the aggregate level, the local labor markets (particularly the manufacturing sector) have been hit hard. Additionally, although the aggregate productivity was very high, the hourly wages remained stable for many workers in the American labor force. This might be due to the decline in employer demand relative to the previous decade, as Holzer and Hlavac (2012) state.

Two remarkable events during 2000-2007 for the U.S. are the stock market bubble burst and the war in the Middle East. The dot-com bubble was particularly harmful to the I.T. workers; for example, Santa Clara County's unemployment rate reached 7 percent in the final period of 2001. In the aftermath of the 2001 dot-com burst, the rest of the American economy had a swifter recovery compared to the tech hubs in the U.S., such as the Bay Area and Silicon Valley. On the latter one, the war or terrorism, i.e., Iraq War after 9/11, has relatively more lagged consequences. Joseph Stiglitz argues that one of the main drivers of the Great Recession is Iraq War, which he believes harmed the economy hugely.

5.4 The Great Recession

The Great Recession is considered one of the most destructive events for the U.S. labor markets since the Great Depression. As Şahin et al. (2014) suggest, structural problems, e.g.: the Mismatch phenomena, became more evident compared to the previous crises and the duration of the unemployment spell has increased substantially. We will discuss these further in the following sub-section about the post-Great Recession.

One interesting finding is that the labor force participation did not fall for women but only for men. Additionally, as Borbely (2009) indicates, employment declines are predominantly associated with men. The fall led to a surge in part-time employment during that time. Borbely (2009) states the increase in wages and earnings increased as much as inflation did during the Great Recession.

One of the major differences between the Great Recession with the COVID-19 crisis is that the job losses (and initial unemployment claims) were gradual during the Great Recession; on the contrary, they were all at once in the COVID-19 crisis. The nature of those crises is fundamentally different and requires attention while analyzing. Still, the COVID-19 turmoil has led to unprecedented consequences in the local labor markets of the U.S. Those consequences will be briefly explained in the following subsections.

Mian and Sufi (2014) investigate the effect of the housing channel on the 2007-2009 drop in employment, i.e., the increase in unemployment. Their findings suggest that the non-tradable jobs have been significantly affected by the net fall in housing prices across the U.S. This is directly in line with our findings on the system-wide connectedness index, which we discuss further in the upcoming section.

5.5 The Recovery: Post-Great Recession

The recovery has been a long and windy road. It took 10 years for the unemployment level to fall below the pre-recession levels. One of the underlying reasons behind it is considered to be a geographic mismatch. As in every economic crisis/ downfall, demographics played a significant role in explaining who was more severely affected by the crisis.

Cunningham (2018) presents that U-6 (the most general measure for labor underutilization) began to decrease in 2010 and became more rapid after 2011. Another useful indicator, the employment-population ratio, indicates that the ratio for men started to increase immediately with the recovery era. It was not the case for women, as the downward trend continued until 2012 for women in the American labor force. In terms of demographics, the black people in the labor force had faced the most severe effects of the Great Recession. On the other hand, during the recovery period, only the black labor force returned to its pre-recession levels in the employment-population ratio.

We stated above the hardest hit sectors from the Great Recession in terms of employment. In the recovery period; sales and office, production, transportation, and material moving and natural resources, construction, and maintenance sectors grew relatively modestly and their levels did not return to the pre-recession levels. On the positive side, service and management, professional, and related sectors have benefited largely from the expansion of the post-recession economy.

The long-term effects of the Great Recession have been discussed by Yagan (2019). He argues that employment and income recovery have not been as successful as unemployment recovery. In his work, he emphasizes the local labor markets and finds local impact heterogeneity within and across different types of the labor force. Other findings include the severity of the Great Recession shock on local labor markets, which are the commuting zones at the paper.

Hall and Kudlyak (2020) disagree with the widespread notion that the recovery from the Great Recession has been slower. They argue that there is a uniform recovery of unemployment for all recessions in the last 70 years, and the misjudgment arises from the most considerable weight being put on the output recovery. Another finding from their study shows that permanent job losses skyrocketed during the Great Recession but fell gradually below pre-crisis levels.

5.6 The Great Recession 2.0: The COVID-19 pandemic

The COVID-19 pandemic has introduced conditions that have never been experienced before by any local labor markets. With people being afraid of the virus and decreasing consumption, the demand shock was combined with the supply shock as there have been state-mandated lockdowns globally. This, in turn, has boosted unemployment very rapidly and the record spike in the U.I. claims has been symbolic.

A person in 2018 would have never thought of using public health policy stringency index and community mobility indexes as strong measures to understand the change in the labor market connectedness across states. With that in mind, we analyzed the COVID era separately, where we also use secondary panel data regressions to understand the change in the interstate connectedness. We only conduct a connectedness analysis on the labor markets; the secondary regressions require pairwise data which extends to the 90s. As a further extension to our current setup, different variables can also be used in searching for the determinants of the 'more general' labor market connectedness.

There are also political aspects associated with the pandemic responses and the consequent economic stagnation. Akovali and Yilmaz (2020) argue that the pandemic response across states has been quite polarized, as more conservative regions tended to have lax public health policies and worsened labor market outcomes.

In terms of a broader comparison, currently, the Biden administration follows a quite contrary monetary and fiscal policy compared to the Reagan administration. Although it would have been interesting to think how would President Biden's policies shape up without a pandemic, his recent stimulus package and good relations with labor unions are definitely in favor of a pro-active government.

A more recent comparison with the Great Recession recovery is necessary at this point. In terms of racial equality, the pandemic recovery period seems to be much more equal. Bayer et al. (2016) point out the problems associated with the over-pronounced effects of housing crises on the racial minorities. Currently, the U.S. economy has the lowest foreclosure rates and it is indeed a much brighter picture than the post-2008 economy. Additionally, according to state-level briefing published on the 4th of May, Montana stands out as a pioneer state returning to pre-pandemic levels in employment. The state government announced its withdrawal from federal U.I. benefits and the launch of return-to-work bonuses. Looking deeper into the state's picture, unemployment levels have reached the pre-pandemic levels and the labor force is almost back.

Chapter 6

NETWORK ESTIMATION RESULTS

6.0.1 Dynamic Estimation of Interstate Labor Market Network: System-Wide Connectedness

We characterize the dynamic interstate labor market network in this section. To capture the dynamics, we employ the rolling sample window analysis. The model is estimated separately for each date using only the previous T observations, where T is the fixed rolling window size. Our analysis in this section is from January 1989 and to October 2020. Figure 6.1 shows us that the connectedness increase during recessions and economically stressful periods and decrease during smoother periods. The connectedness reacts with a lag. This can be seen from the Great Recession, where the connectedness drops in 2008 and starts to increase dramatically by late 2008.

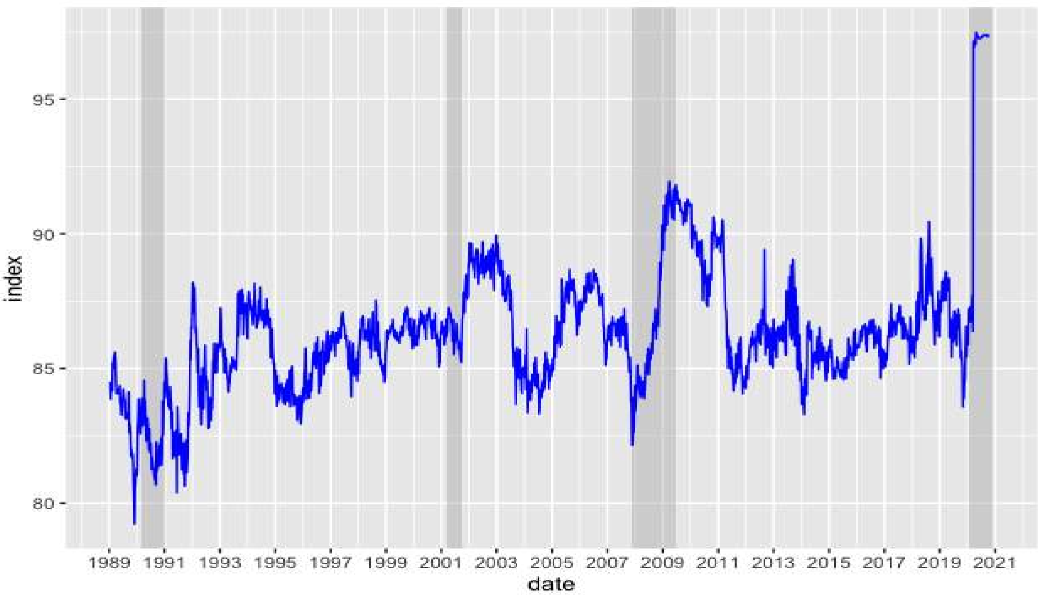

Figure 6.1: System-wide Connectedness of State-Level Initial Unemployment Claims

There are immediate observations in the Figure 6.1. The system-wide connectedness allows us to understand the problematic periods for the local labor markets in the U.S ,

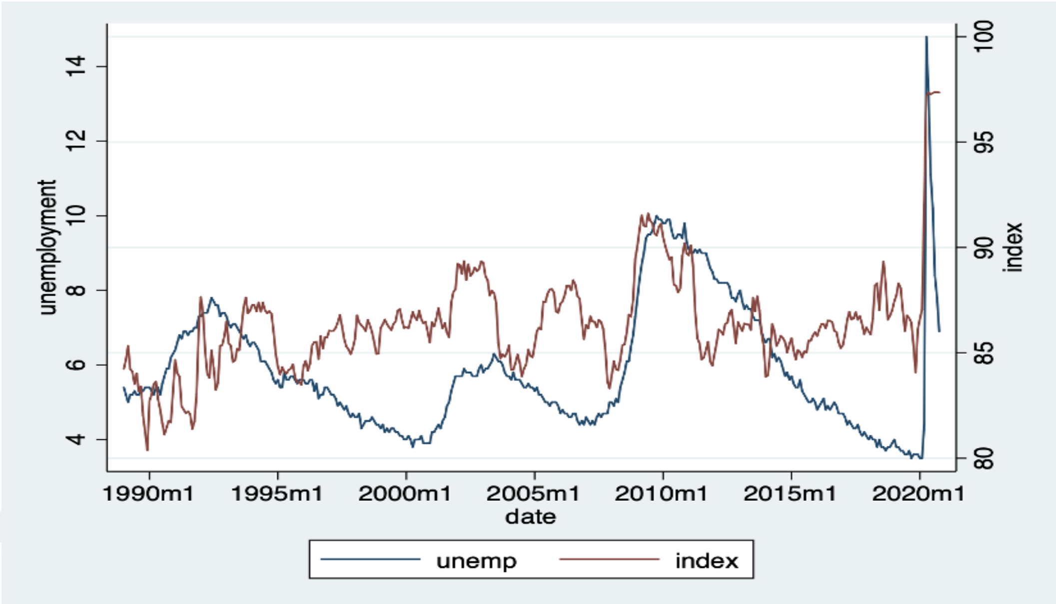

Figure 6.2: System-wide Connectedness of State-Level Initial Unemployment Claims with Unemployment Rates

which we will discuss in detail below. The periods are partitioned annually.

There have been coordinated market interventions which correspond to the end of 1980s. These developments follow right after the Volcker Recession, including Plaza Accord in September 1985. Volcker Era meant all-time-high effective federal funds rate, and consequently large increases in unemployment and inequality. As it can be seen in Figure 6.1, there has been a gradual downfall to connectedness level of 80. This level has never been reached after that time period, it increased only.

The U.S. faced a recession starting in 1990. The most pronounced effects of that recession can be seen around early 1992; the late recovery from that recession is considered as one of the driving factors for Bill Clinton's election during the 1992 Presidential Elections. There are underlying factors that explain the relative volatility of the unemployment connectedness during the early 1990s. Nadrone et al. (1993) argue that the big cuts in military spending during the early 1990s have been influential in the volatile and lagged recovery in the labor markets. This, in turn, affected other sectors and led to a net loss of 858,000 jobs in the U.S. Gardner et al. (1994) state that the labor market improvement has been better in 1993 than 1992, but the labor decline in manufacturing continued and adversely affected the recovery period. There are two things that are common in 1991-1993: The decline in manufacturing industry and high volatility in consumer confidence index. We believe that these two are crucial in the volatile recovery after the Early 1990s Recession. On the other hand, the recession proved to be short-living and the economy returned to its 1989 connectedness levels by early 1995. Another contributor to the problematic recovery, which is also discussed by Nadrone et al. (1993), is the weak exports due to global economic problems, particularly associated with Japan and Eurozone. As we discussed above, the remaining of the 1990s have been relatively calmer and the economy has faced unprecedented productivity growth and unemployment rates. This period corresponds to the so called 'Roaring Nineties'. This period is well known with the globalization and increasing connectedness across nations. This led to a global increase in productivity and optimism in the markets. Increasing power of technology (in particular, the personal computer boom), the fall of communist governments and financial integration were other drivers of this fruitful decade. Contrary to Nadrone et al. (1993), although a mild recession, according to Gardner (1994), the labor markets did not heal for a long time although the other indicators of the economy returned positive long after the 1990s recession. Gardner (1994) also stresses the fact that the long-standing peacetime expansion and the crisis came across at the same time. Additionally, more industries have faced the consequences of deterioration in labor markets compared to the previous recessions. For instance, Gardner (1994) argues that white-collar workers (in the finance, insurance and real estate industries) have experienced a much greater risk of job losses than the previous recessions. Finally, she states that a substantially smaller number of unemployed workers have returned to their jobs compared to the previous recessions.

During the early 2000s, the U.S. faced another recession. According to Langdon et al. (2002), although the Asian Financial Crisis did not lead to ripple effects to the U.S. economy, the burst of the stock market bubble has affected the economy tremendously. This, in turn, led to a big increase in unemployment connectedness between 2001 to 2003. Since the beginning of our timespan, 1989, the system-wide connectedness reached its peak in early 2002. The increase after 2005 in unemployment connectedness is also worth attention. This is related to the first burst of the housing bubble, and it stabilized for a while before the Great Recession truly began. The subprime market was less than 9 percent in 2002 and reached 25 percent by 2005. There are two falls until 2008, particularly in mid-2006 and 2007. In 2008, as the Great Recession began, the unemployment connectedness jumped to very high levels. There has been a big surge from the beginning of 2008 to mid-2009. As we discussed above, the recovery has been long-standing and the system-wide connectedness has never fallen to the pre-crisis levels afterward. Studies such as Şahin et al. (2014) argue that there are also structural elements that prevented a swift recovery after the Great Recession, which is also referred to as 'mismatch'.

There has been a small, but eye-catching, increase from late 2018 to 2019. The recovery is evidently within a shorter time span, and the connectedness levels are closer to 2015. What are the underlying reasons behind this increase? It corresponds to the mild manufacturing recession in the United States before the pandemic. Additionally, U.S. President Donald Trump had strained relations with China and fear of trade war was felt within the international markets. Other reasons outside of the Trump administration were low oil prices, decreased auto sales and a high exchange rate with the valuable USD. Global signals included the slowdown of the German economy and uncertainty in the British economy due to Brexit.

Unlike the Great Recession, the COVID-19 pandemic has its effects on the American labor markets immediately. With the first cases of COVID-19 in the U.S., the connectedness index reaches a completely different level. The index reaches a new dimension and discussing it in the same graph with the previous events is not suitable. Therefore, we end our system-wide connectedness analysis there. The level indeed shows us the major effects of the pandemic on labor markets and how rapid its effects were felt in the U.S. state-level labor markets.

One important pattern to note is the higher persistence of the crises as we come closer to 2021. The recovery pattern does not show such a pattern, yet once the connectedness increases, it stays more at that level for a longer time. It is a big interest to see in the upcoming years whether the COVID-19 pandemic will lead to a very high persistence in the high connectedness levels. In addition to these, the local labor market connectedness has never reached its levels in the 90s. Taking out of all the recessions and pandemic out, the decrease of routine jobs and globalization are significant drivers of such a trend. One of the most considerable effects of those shocks was felt in 2000 and 2001, particularly in regions with higher manufacturing jobs like Midwest. These periods correspond to the new millennium's first months and the stock market bubble and the first introduction of severe import competition by China to the U.S. The Iraq War after 9/11 and substantial military spending for years in Iraq and Afghanistan during the Bush Administration were also big hurdles for the economy itself during that period, and the connectedness levels persisted quite a lot during those years.

In Figure 6.2, the relation between unemployment connectedness and unemployment levels at the national level are presented. For most of the time, an increase in unemployment is accompanied by a higher and volatile connectedness index. An exception to them is the 2005-2007 period, which we believe is due to the high energy prices, where the connectedness levels increase while the unemployment rate decreases. Another example of that is the mild recession in the late 2010s during 2018-2019. We believe that is also a sectoral recession, i.e., a manufacturing recession, coupled with the uncertainty introduced by the Trade Wars between the U.S. and China.

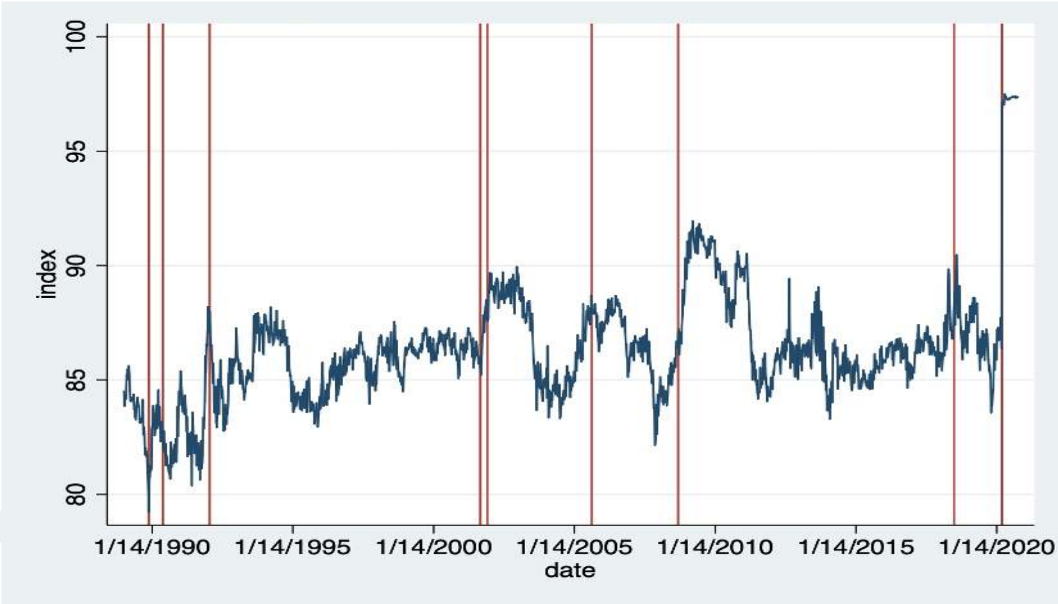

Figure 6.3: System-wide Connectedness of State-Level Initial Unemployment Claims with Important Events

In Figure 6.3, we present important events in the systemwide connectedness index. Although we explained the system-wide connectedness time series in a detailed fashion above, we will briefly explain each event. The first event is not an event per se but the lowest connectedness level of the last three decades. We believe that this is due to the expansionary monetary policy followed by the FED after the Volcker Era. The second event corresponds to the Early 1990s Recession. The third, and the last of 1990s, event corresponds to the lowest consumer confidence levels in early 1990s and a proof for the jobless recovery after the crisis.

The first event plotted in the 2000s is the terror attacks in New York City, 9/11. The fifth event in Figure 6.3 is the date of China's entry to the WTO. This is crucial in the context of the introduction of import competition, which we discussed extensively above. The sixth event, the third in the 2000s, is Hurricane Katrina. Although only regional, instead of the national unemployment rates, did increase substantially in that period, we see an increase in the system-wide connectedness. However, as we explained above, this period corresponds to the first burst of the housing bubble. We believe that it has been quite influential, having close dates with Hurricane Katrina. The final event of the 2000s is the bankruptcy of Lehman Brothers. The official default was on the 15th of September, 2008. The closest date for that date in our weekly connectedness index is the 20th of

September, 2008.

Finally, in the 2010s, 2020 and 2021, we present two major events. One of them corresponds to the China-U.S. Trade war, which the former U.S. President Donald Trump initiated. The official date for introducing American tariffs on 34 billion dollars of Chinese goods was the 6th of June, 2018. The closest date for that date in our weekly connectedness index is the 9th of June, 2018. The ultimate event is when we begin our analysis in the COVID part of the paper, the 21st of March, 2020. The connectedness index skyrockets on that period and we take that period as a reference in analyzing the pandemic state of the American economy.

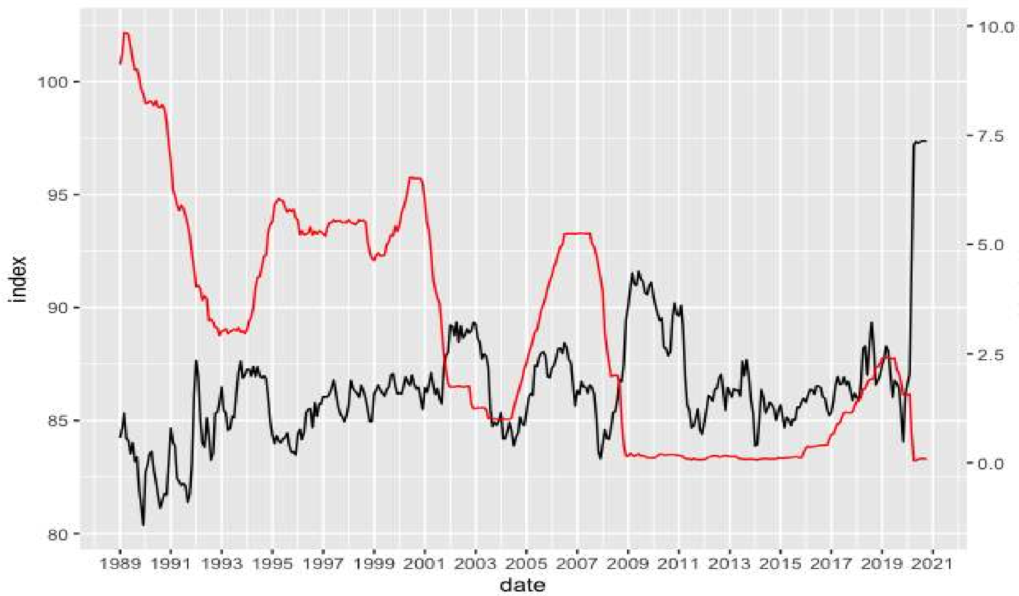

Figure 6.4: System-wide Connectedness of State-Level Initial Unemployment Claims with Federal Funds Rate

In Figure 6.4, we present the association between monetary policy stance and the unemployment connectedness. The FED employed the money supply targeting mechanism in 1979. However, the most significant first step for transparency corresponds to February 1994, when FOMC kick-started publishing policy statements regarding the overnight federal funds rate.

Paul Volcker raised interest rates considerably during his early terms to fight high inflation, above 10 percent in 1980. A more extensive discussion of the Volcker Era can be found above. Our system-wide connectedness includes the terms of Alan Greenspan, Ben Bernanke, Janet Yellen and Jerome Powell.

High interest rates characterize 1989 and 1990. Although the economy had relatively high inflation in 1990, the FED lowered the interest rates. We see a gradual decrease in the interest rates, yet the connectedness index increased with ups and downs (in an irregular fashion). One reason was the financial crisis in 1990. Another reason is the Gulf War, an event that was triggered by Iraq's invasion of Kuwait, which indirectly affected the labor markets in the U.S. As we discussed above, 1992 represents the jobless recovery phenomena in the post-Early 2000s Recession economy. To fight with it, the FED lowered the interest rates. During Clinton Administration, from 1993 to 2001, the FED had a balanced policy and the economy had a fruitful period, which is widely known as 'Roaring

Nineties'.

After George Bush took office in January 2001, the economy faced a recession in March 2001. Consequently, with 9/11 added on it, the economy had difficulties recovering, and the FED kept interest rates low until Summer 2005. Other policies to stimulate the economy included The Jobs and Growth Tax Relief Reconciliation Act in 2003. Although the FED lowered interest rates to stimulate the economy against the recession, the increasing uncertainty with the War on Terror and fall in demand in the economy have fueled the unemployment and its interstate connectedness. We see an increase in the connectedness index for a year starting from May 2004. Although unemployment did not increase per se, the index shows that contractionary monetary policy positively affects the index. When we look at the to connectedness of each state around late 2004 and early 2005, we see that states that are the biggest energy producers had significant increases in their to connectedness. These states include Alaska, North Dakota, Kansas, Colorado and Arizona. Therefore, we believe that this increase in connectedness was due to the energy crisis in the 2000s. Crude oil prices reached to all-time-highs in 2003, 2005 and 2008.

The first signals of the Great Recession were in 2007, particularly in the housing market. The recession led to an era with interest rates close to 0 for 7 years, between 2008-2015.

From 2015 to 2018, the FED kept increasing the interest rates. By the end of 2018, the FED decided to stop raising rates any further. We see small spikes in the index, which is reactionary to the monetary policy. The increases are also associated with the global slowdown in the economy and the uncertainty brought by the Trump administration on the affairs like global trade. We discussed the silent but impactful recession during 2018-2019 above. Finally, with the COVID-19 pandemic, the FED returned to the emergency state of monetary policy by lowering the rates to 0.25 percent. As of July, the FED has not made any changes in its approach.

There is a further debate regarding the validity of the Philips Curve in modern macroeconomics. Although there have been previous well-known studies in the subject, such as Blanchard (2016), Hazell et al. (2020) come up with a new extensive dataset. In that regard, Hazell et al. (2020) investigate the slope of the Philips Curve by building up a new dataset on state-level price indexes for non-traded goods and services. Their estimations suggest that the slope of the Philips Curve has been rather small. In other words, they find that Philips Curve is not dead, i.e., a higher employment rate leads to higher inflation, but it is quite modest compared to what traditional theory predicts. Our results support their hypothesis, connectedness in stressful periods remains high and volatile, relatively invariant to the monetary policy channel in the traditional Philips Curve theory.

6.0.2 Dynamic Estimation of Interstate Labor Market Network: Interregional (Conditional/Pairwise) Connectedness

In this section, we embed pairwise connectedness across states into the picture. To that end, we use the annual averages of network weights across states, which corresponds to 2601 entries per year. Then, we use dummy variables for the respective regions of the source and target states. By doing so, we aggregate the to, from and net connectedness of 51 states and the associated regions[1].Furthermore, we aggregate these by the regions of each state; and get a $4x4$ variance-covariance matrix. For net connectedness, we do not go through the diagonal elements as the diagonals are all zero. This is expected since the to and from unemployment within a region are equal to each other.

This subsection answers two questions: Which regions have more influence on each other and how it evolves over the three decades? Although system-wide connectedness explains many things, interstate relationships are missing out of the picture. The flows across regions are particularly important in identifying the relatively more minor shocks, such as local shocks. Additionally, we believe that the sectoral breakdowns are better understood by inter-regional connectedness analysis. In all four regions, some sectors dominate that respective region, and a downfall in those sectors directly reflects on their regional economic performance. In the following subsections, we will briefly analyze the net connectedness dynamics between all regions. Since the net connectedness is symmetric between regions, here we only present three figures. This is purely for simplicity in presenting.

[1]The number of rows is 205 here. We aggregate the regions for each state. We still have all 51 states in our analysis.

Figure 6.5: Net Connectedness between Northeast and All Other States

Before going through our analysis, the reader should note that the Northeast region is also referred to as New England by several sources. One immediate observation from Figure 6.5 is the net unemployment receiving position of West and Midwest regions. Both regions have almost always received unemployment from the Northeast. In particular, it generated more net unemployment connectedness to those regions during crises in the last three decades, such as the early 2000s Recession, the Great Recession and the late 2010s, respectively. On the other hand, the South has generated net unemployment connectedness to the Northeast until 2001. We believe that this trend is due to low oil prices in the late 1990s, where we see the peak net unemployment connectedness from South to Northeast in 1998. The dip in oil prices was primarily a result of the East Asian Financial Crisis in 1997. As the energy sector started to heal in the late 1990s-early 200s, we see a corresponding increase from 1998 to 2002 in the South's net connectedness to the Northeast (not in absolute terms).

There is a convergence in the triple time series between 2012 and 2016. South has the biggest range between these three states. During the 1990s, the Northeastern states received unemployment connectedness from the South, which altered around 2006-2007. However, the South has almost always received less unemployment connectedness than what the West and Midwest received. We see a spike in all three time series by 2016; the Northeast generates net unemployment connectedness to the South, West and Midwest.

Irwin (2018) argues that 2015 and 2016 correspond to a silent yet an impactful crisis. He argues that the main reasons for the silent economic crisis have been the drop in commodity prices, increase in the value of the dollar and stagnating business investment. The energy, agriculture and manufacturing sectors have been hit the hardest. These industries are crucial for the Northeast. According to Deming (1996), Northeastern states faced stagnant growth rates during 1983-1995 and there has been a considerable amount of migration to West and South from Northeast and Midwest states. Although we see an increase in both regions' (West and South) time series at Northeast (not in absolute terms), this is not directly consistent with Deming (1996) in that regard.

Northeast almost returned to its 1980 unemployment percentage levels by 2014, around 6.2 percent. According to American Community Survey (ACS) in 2017, California, Texas and New York had the highest out-migration in 51 states. Florida, Texas and California had the highest in-migration. The Current Population Survey (CPS) in 2018 also reflects South had the main importance in to and from migration at a regional level. The reader should be aware that internal migration does not directly associate with unemployment, yet we believe that it is indirectly associated with unemployment spillovers. Due to endogeneity concerns, we do not integrate in and out-migration to our secondary regression analysis (at the COVID-19 part of the paper). We believe that higher unemployment connectedness might drive the migration trends and vice versa.

Figure 6.6: Net Connectedness between South and West and Midwest

South has been in giving and receiving positions with the other three regions in the last thirty years. South has been generating more unemployment connectedness to Midwest than it did to the West during most of the 1990s. Although South has generated net unemployment connectedness to both regions in most of the 1990s and 2000s, the trend changes for Midwest by 2014. We believe that the net unemployment connectedness trend by South to the other regions is due to the very low oil prices throughout the 1990s, which we briefly described above. This can be seen from net connectedness between the West and Midwest (with South). Having peaked in 2002, the net unemployment connectedness decreases for Midwest (with South). Starting from 1995 and 1998 (for Midwest and West), both regions had an increasing trend in net connectedness with South (not in absolute terms) until 2002-2003. For both regions, this is due to the increasing to connectedness. In other words, during that time period, the South generated more net unemployment connectedness to West and Midwest regions than it did in the previous years.

Like Northeast, we see a change in the time series of South and West and Midwest. Midwest generates net unemployment connectedness to South from 2016 to 2019. The same follows for West as well, however, to a lesser extent. West outperformed the rest of the regions. According to the report of the Census published in 2020, West and South have been the most attractive regions in the U.S. According to that report, the South had a population growth rate of 10.2 percent in the last decade, followed by West at

9.2 percent. The same report states that almost all of the 10 fastest growing states (in terms of population) are from West and Southern states, with the first one being Utah. There is a striking difference in the growth rates between South West and Northeast Midwest. In the last decade, the Northeast had a population growth rate of 4.1 percent, followed by the Midwest at 3.1 percent. West's employment has grown more than the rest of the regions, and the service sector jobs with relatively higher wages, have created a comparative advantage. Having a diversified economy, the West had mostly received net unemployment connectedness from other states.

Figure 6.7: Net Connectedness between Midwest and West

Finally, in Figure 6.7, Midwest received unemployment connectedness from the West during the 1990s. After 1990, the trend starts to reverse and by 1992, Midwest almost always generates unemployment connectedness to the West. When we consider Figure 6.5 and Figure 6.6, for the majority of the time span, West received unemployment connectedness from all other regions. Until the 1990s, Midwest has been the champion of all major regions in the U.S. It has achieved full employment trends with its rapidly growing industries. Midwest economy has been one of the main drivers of post-war economic success in the United States. However, as indicated by Deming (1996) and Holzer and Hlavac (2012), Midwest states' success story diminished starting from 1990s. The main reason for this downfall is due to the sectoral dynamics, especially in the manufacturing sector. In addition to these, we see a spike in the net unemployment connectedness from Midwest to West in 2016. As Irwin (2018) indicates, the mini-recession severely affected the manufacturing sector. Midwest, traditionally known as a manufacturing hub, is also significantly affected by this mini-recession, leading to a spike in its net connectedness with the West.

As we explained above, West had been the best performing region by its multifaceted economy. Midwest lost its grounds to other regions throughout these three decades, primarily due to automation and import competition introduced by China's accession to global trade. South had a downfall during the late 1990s due to the decreasing oil prices.

The main force in the Southern economy, Texas, is the biggest crude oil producer in the country. Northeast, hosting the major counties for the higher-skilled labor force, had a poor performance in the last thirty years, particularly after the mid-2000s. We see the highest net unemployment connectedness generation from Midwest to South in 2002-2003, with a reversed pattern after 2014. The second highest unemployment connectedness corresponds to the 2010 levels of West and Northeast. We believe that the first one is due to the high oil prices in the global economy. The second one is due to the Great Recession. However, we don't see such net unemployment generation to Midwest by Northeast, West and South. In other words, the other regions received net unemployment connectedness from Midwest during the Great Recession. The midwestern economy had faced its biggest challenges in 2001 and it poorly performed until 2007. Midwest suffered more from the structural changes in the U.S. economy in the early 2000s than the Great Recession in 2008. In retrospect, wage growth and employment dynamics are the main signals of the downfall in the Midwestern economic success story.

Chapter 7

NETWORK STRUCTURE OF UNEMPLOYMENT CONNECTEDNESS ON VARIOUS PERIODS

In this section, we will present the network structures which correspond to the crucial periods that were presented in the dynamic index figures. We will present nine different network graphs for nine different periods. The network graphs consist of full sample, i.e., 51 states. However, unlike Bostanci and Yilmaz (2020), we will not use a day after the event for the comparison of network graphs. This is due to the more lagged nature of unemployment response compared to sovereigns.

Before going through the analysis, it is worth noting that we present trim the weaker edges to increase the visual representation of the networks. Secondly, as mentioned in the previous papers using DYCI and network graphs, the network graphs are presented for reader to gather the first inference. Still, the reader is highly encouraged to go through the numerical results for the associated analysis.

7.1 1990s

We firstly present the first spike in the 1990s, which corresponds to February 3rd of 1990. Figure 7.1 is during the first spike after the downfall in January 1990. In Figure 7.1, the Northwestern local community structure can be seen on the upper right side of the network graph. Same local structures can be found in different parts of the graph, e.g., lower left side of the graph consists of Southern states.

A very straightforward observation is readily available: The states with the highest eigenvector centrality are mostly Midwestern states, which can be seen in light brown, bright and dark red colors. The node colors are adjusted according to the weighted-out-degree, i.e., the more affected states are with red (and darker) colors and the ones which are least affected are with green (and lighter) colors.

In Figure 7.2, we observe that the local structures embedded in Figure 7.1 are not available. In 1992, all the states with bigger labor markets were severely affected by the early 1990s recession. These include California, New York and Texas, which had yellowish

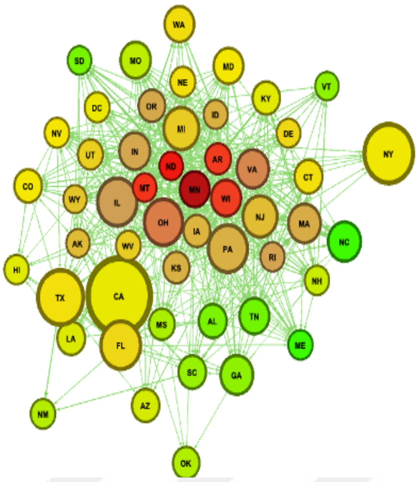

Figure 7.1: Network Graph for Unemployment Connectedness, 03.02.1990

colors. The node sizes are adjusted according to the monthly Non-Farm Employment Data by St. Louis FED. We take the annual average of Non-Farm Employment for each state and calculate the node sizes as a simple measure for labor market size. Although more states are affected, which can be seen from the node colors, there is no piling up in central as in Figure 7.1.

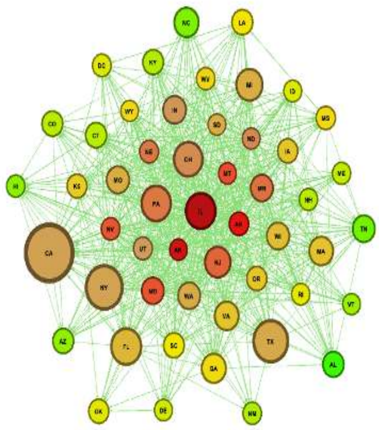

Figure 7.2: Network Graph for Unemployment Connectedness, 07.03.1992

Finally, from a relatively calmer period, we have Figure 7.3. The states with bigger labor markets are less affected, they are relatively in the periphery of the network graph. There are some local structures again, for example, Southern states are in the left middle of the graph. Yet, it is not as much as Figure 7.1.

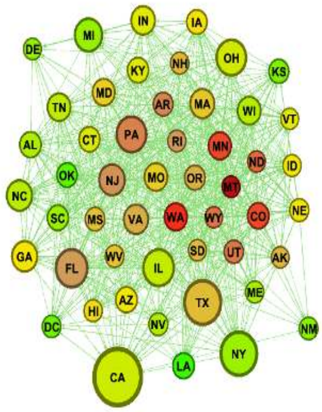

Figure 7.3: Network Graph for Unemployment Connectedness, 14.10.1995

7.2 2000s,2010s and 2020s

We begin by choosing early 2002 (Figure 7.4) to our network graph analysis because this period corresponds to the second largest system-wide connectedness index level in the 2000s, after the Great Recession. Again, several Midwest states are highly affected with high weighted-out-degree and eigenvector centrality. The biggest labor markets, California, Texas, Florida and New York, are similar to their levels in 1992.

In our second figure from the 2000s, Figure 7.5, we have local structures of various regions. For example, the smaller regions of the Northeast (and less affected from the Great Recession) can be found on the upper right of the Figure 7.5. All the biggest labor markets, mentioned in the above paragraph, are bad to severely affected. Figure 7.5 includes the primary scenario with one of the biggest labor markets, Texas, being severely (red color node) affected.

In our ultimate network graph, Figure 7.8, we have the network graph for the latest date included in our analysis, February 27, 2021. As it is seen in Figure 7.8, there are very high connectedness levels almost at all and across states. All states are severely affected

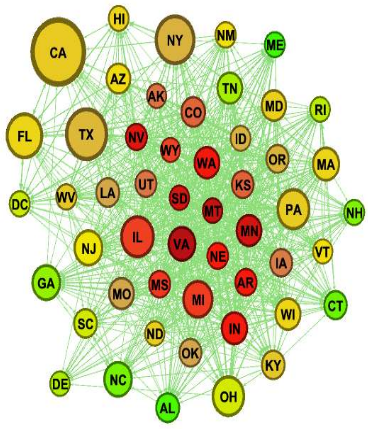

Figure 7.4: Network Graph for Unemployment Connectedness, 16.02.2002

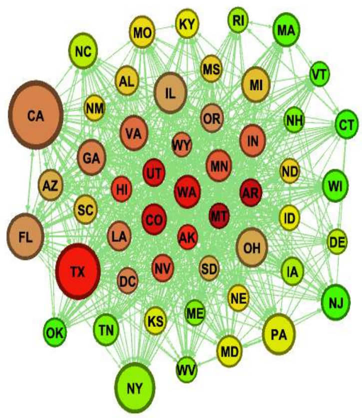

Figure 7.5: Network Graph for Unemployment Connectedness, 09.05.2008

by the crisis, which can be seen from their node colors. The edges are very dense, although we trim them as we did for the other network graphs. This confirms that COVID-19 shock has been an almost uniform shock on all states, affecting all of them (albeit not equally). The very central state is Nevada, and this requires further notice. As one of the states with the highest amount of service sector workers, Nevada had been hit worst with the past public health policies and lockdowns to prevent the spread of the COVID-19 pandemic throughout 2020 and early 2021 in the U.S. The spread of virus and heterogeneity in the pandemic response of the states mattered a lot too.

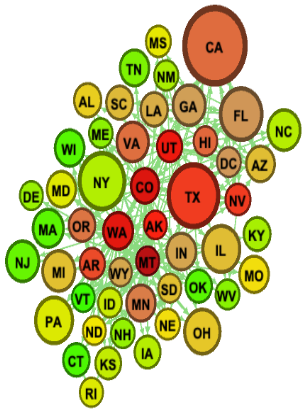

Figure 7.6: Network Graph for Unemployment Connectedness, 14.03.2009

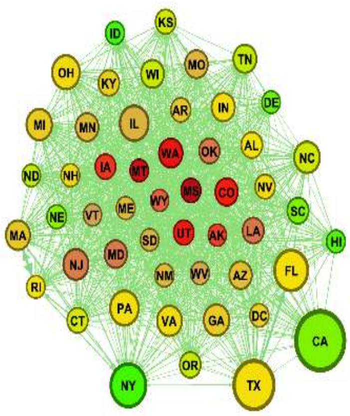

Figure 7.7: Network Graph for Unemployment Connectedness, 14.10.2017

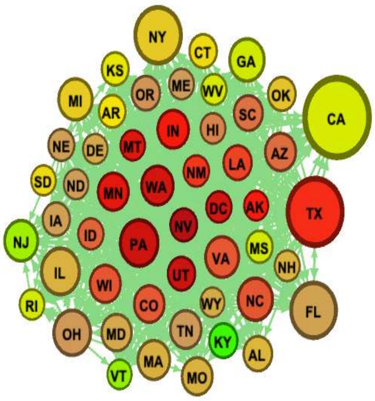

Figure 7.8: Network Graph for Unemployment Connectedness, 27.02.2021

Chapter 8

LABOR MARKETS AND STATE-LEVEL GOVERNMENT AND COMMUNITY RESPONSES

Before going ahead with the analysis of labor market connectedness across states, in this section, we first aim to study the relationship between the state-level COVID-19 cases, the government policy and community responses to the pandemic, and the growth rate of initial unemployment claims.

As the number of UIC increased substantially since the beginning of the pandemic, it is quite normal to expect the increased number of COVID-19 cases to lead to higher unemployment with a lag of several days to one week or longer. However, this relationship may not be uniform across all states. In some states, despite the increase in COVID-19 cases, the government and society did not prefer to make drastic changes in their economic activity and social life. As a result, it is quite possible not to observe a drastic increase in UICs even when the number of new COVID-19 cases increases significantly. As shown by Akovali and Yilmaz (2020), this is especially true for the states with Republican governors.

Considering this fact, we conjecture that along with the COVID-19 cases, the state government policy and the community mobility response to the pandemic are also crucial determinants of the economic activity and hence the initial unemployment claims. Consequently, we expand our empirical analysis of the potential determinants to include the government policy and community mobility responses to the pandemic as other RHS variables in our analysis of the determinants of the UIC in the COVID-19 era. We use the government stringency index (GSI) and Google's Community Mobility Indicators (CMIs) as measures of government policy and community responses during the pandemic, respectively.

Before presenting our results, it is crucial to note an econometric specification issue that may affect our estimation results. There is a potential multicollinearity problem among the right-hand side variables, namely, the 7-day average new COVID-19 cases, the government stringency index, and the community mobility indicators. As the state governments take stricter public health policy measures, the GSI, which measures how stringent is the government policy against the COVID-19 pandemic, increases. Simultaneously, however, tougher government policy measures are likely to limit the community's ability to use public spaces as freely as before. Consequently, one must be careful in using these two variables as explanatory variables simultaneously in a regression.

There is also the possibility of a multicollinearity problem in using the lagged COVID-19 cases along with the lagged GSI and CMI variables; as the number of cases increases, the state governments are likely to take stricter public health policy measures, which leads to a higher GSI with a lag. Similarly, as the number of cases increases, the community members restrict their use of public spaces, which leads to a decline in the CMIs measuring public space use.

As the UIC data are observed weekly, we also convert our daily observed RHS variables to weekly frequencies. Furthermore, to make all the data stationary, we use weekly rates of changes of all variables used in the analysis. While it is easier to define the weekly rates of changes of initial claims, government stringency index, and average community mobility indicators, in the case of the new COVID-19 cases, we follow Akovali and Yilmaz (2020) and use weekly growth rates of 7-day average new COVID-19 cases. We need to make this slight adjustment because the irregularities in the announcement of the COVID-19 cases can lead to too much noise in the daily data.

To avoid the multicollinearity problem, we regress both the GSI and average CMI (ACMI) variables on the 7-day lagged growth rate of the 7-day average new COVID-19 cases, along with their respective lags. We take the residuals from these two regressions and use them as the right-hand side variables.

The fixed-effect regression results for the period from March 21, 2020, to May 1, 2021, are presented in Table 8.1. The explanatory power of the regression is not very high and decreases from 0.372 to 0.316 as the number of lags of the explanatory variables increases from one to three weeks.

Let us start with the coefficient estimates of the new COVID-19 cases. The adjusted weekly growth rate of new COVID-19 cases lagged one- to three-weeks have statistically significant effect on the weekly rate of change of initial unemployment claims. A 10% percent increase in the one- to three-week lagged growth rate of the new COVID-19 cases lead to 0.07 and 0.05 percent increases in the UI claims growth rate, respectively. This is quite a small effect; however, it is also possible that the government and community reactions to the pandemic potentially had a substantial impact on UIC.

	–Lag One–	–Lag Two–	– Lag Three –
COVID lagged	0.007*	0.006*	0.005*
	(0.003)	(0.003)	(0.003)
ACMI lagged	-2.754**	-2.445**	-2.239**
	(0.319)	(0.298)	(0.284)
GSI lagged	0.949**	0.803**	0.686**
	(0.114)	(0.117)	(0.114)
Number of Obs.	2,387	2,336	2,285
Adjusted R^2	0.372	0.342	0.316

Table 8.1: Panel Regressions, Initial Claims on CMI and GSI

Notes: Standard errors in parentheses. + $p < 0.1$; * $p < 0.05$; ** $p < 0.01$

In our UIC panel regressions, both the GSI and average CMI variables' weekly growth rates have statistically significant coefficient estimates. The same conclusion above (for the COVID variable) also holds for the GSI and average CMI variables, i.e., as the number of lags increases, the coefficient estimates decrease (in absolute value). Additionally, as the number of lags increases from one to three weeks, the goodness of fit decreases from 0.372 to 0.316.

The coefficient estimates of all three lagged weekly GSI growth rates are positive, as expected. More stringent government policies towards the pandemic reduce the growth of new COVID-19 cases. Still, the results show that they also increase UI claims, as they affect the state-level economic activity adversely. As the government stringency index increases 10%, the initial unemployment claims increase by 9% within a week, and 8 to 7 % within two to three weeks.

Table 8.1 also presents the coefficient estimates for lagged values of the growth rate of the average CMI indicator. As expected, the coefficient estimate of ACMI is negative, and decreases in absolute value from -2.8 to -2.2 as the number of lags considered increases from one to three weeks. A drop in ACMI implies a decline in public space used by the community, which would imply a reduction in economic activity, hence an increase in the number of workers losing their jobs. A 10% increase in ACMI implies a 28% increase in unemployment claims in the first week. The effect declines down to 22 % three weeks later.

We also estimate this relationship between the UICs and the explanatory variables for each state. In all but two states, COVID19 cases do have statistically significant and positive impact on UICs. The signs and statistical significance of the GSI and ACMI coefficient estimates vary substantially across the U.S. states. 20 and 16 of the 51 states do have statistically significant coefficients estimated with the expected signs of ACMI and GSI, respectively.

8.1 Pairwise Connectedness and Panel Secondary Regressions

This section analyzes the factors that can contribute to the connectedness of labor markets across states. To identify factors that contribute to pairwise connectedness across the U.S. states, we estimate panel data regressions of the following form over the full sample (starting from March 21, 2020 through May 1, 2021):

$$\tilde{\theta}^g_{ij,t} = \beta_0 + \beta X_{ij,t} + \alpha_j + \gamma_i + \tau_t + u_{ij,t} \tag{8.1}$$

where $\tilde{\theta}^g_{ij,t}$ is weekly directional pairwise connectedness from state j to state i. $X_{ij,t}$ denotes a set of regressors that can include the sum of weekly COVID-19 cases in state j relative to state i (normalized to the total number of COVID-19 cases in our full sample), average Community Mobility Measures (CMI) in state j relative to state i, Government Policy Stringency Index (GSI) in state j relative to state i, the log distance between state i and j, log trade flows (i's exports to j and i's imports from j) and region dummies for U.S. states. γ_i,α_j and τ_t are the source, target and time fixed-effects, respectively.

It is an essential matter of interest to discuss the variables in our panel data regressions. CMIs represent the ratios of community mobility indicators for the source and target states. They show how community preferences on public space usage vary across the U.S. states. The CMI measures include the use of transit stations, workplaces, groceries and pharmacies, and residential places. Many of the substantial decreases in community mobility were due to state-level lockdowns. Lockdowns are one of the strictest public health policy measures that negatively affect the labor markets in the associated states. The number of COVID-19 cases and its causal relation with CMIs were analyzed in different articles, including Wilson (2020) and Wang and Yamamoto (2020). To the best of our knowledge, no study tries to understand the effects of average CMI on labor market outcomes.

To understand the effect of different public policy measures on labor market outcomes, we include public policy stringency index ratios for associated states. The stringency index is one of the main factors determining the number of COVID-19 cases, hence included in our pairwise secondary regressions.

As stressed out in Akovali and Yilmaz (2020), there might be a possible multicollinearity problem concerning the average CMI and stringency measures. Many state governments introduced new restrictions as a response to increasing COVID-19 cases. Therefore, two of our explanatory variables in the secondary regressions are highly linearly related. To overcome the multicollinearity, we apply state-level regressions for average CMI on the 7-day moving average new cases, like Akovali and Yilmaz (2020). The residuals from those regressions are used as the community and stringency measures, which are assumed to be orthogonal to the unemployment insurance claims.

As another variable of interest for COVID-19, we add log of the normalized COVID-19 cases ratio to our secondary regressions. This variable is the log of the ratio of the weekly COVID-19 cases for source and target states, normalized with their total COVID-19 cases, respectively. This variable allows us to gauge whether COVID-19 cases affect the labor market outcomes directly. Those states that experience a surge in the number of COVID-19 cases may spread the virus to other states that tend to have a relatively lower number of cases to begin with. This variable allows us to gauge whether those states with a relatively higher number of COVID-19 cases also spread the resulting increase in unemployment to states with lower COVID-19 cases. We expect an increase in the source to target state ratios of log normalized COVID-19 cases to positively affect pairwise interstate labor market connectedness. The higher the COVID-19 cases in the source state relative to the target state, the more likely it would be for the source state to have a higher unemployment rate. Therefore, we expect the unemployment to spill over from the source to the target state, not the other way around. We chose normalized weekly COVID-19 cases instead of COVID-19 cases' growth rate as an explanatory variable because there are negative growth rates, making log variables mathematically wrong.

In addition to the variables we have already discussed, namely average CMI, stringency index, and log normalized COVID-19 cases, we add log distance between states as a RHS variable in our secondary regressions. Intuitively, we expect the pairwise labor market connectedness to decrease as the distance increases.

We also add the log shipments from the target to the source state relative to the shipments from the target to all other U.S. states[1] This variable intends to measure the relative importance of the source state for the target state as a market destination. We expect the pairwise labor market connectedness to increase as the log shipment ratio increases. The more important is the source state for the target state as a market destination, the higher would be labor market connectedness from the source to the target state.

Ultimately, we try to capture the additional regional component associated with the interstate labor market connectedness. Although we have distance as a crucial determinant of connectedness, adding region indicators would allow us capture regional differences in the integration of labor markets across the U.S. To that end, we follow the U.S. Census Bureau's classification for U.S. regions, consisting of four regions: the Northeast, the South, the West and the Midwest.

The COVID-related variables (normalized COVID-19 cases, ACMI, and GSI) vary across pairs of states and over time, which allows us to follow their possible effects on pairwise connectedness. The shipment rate ratio and the distance between states vary across pairs of states. All regressions are level-log regressions; in other words, the dependent variable is in levels, and all independent variables are in logs. Pairwise connectedness measure varies between 0 and 100; for that reason there is no need to take the log of it to smooth out wild variations in data.

[1] For the construction of this variable, we subtract the internal (*in-state shipment*) shipment from the total shipment made from the source to the U.S.

Variables	Lagged One Week			Lagged Two Weeks			Lagged Three Weeks			Lagged Four weeks		
COVID	0.003	0.003	0.003	0.006*	0.006*	0.006*	0.007*	0.006^{+}	0.006*	0.010**	0.009**	0.010**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
ACMI	-0.194**	–	-0.194**	-0.056	–	-0.028	-0.119**	–	-0.083*	-0.150**	–	-0.124**
	(0.040)		(0.041)	(0.040)		(0.041)	(0.038)		(0.038)	(0.036)		(0.037)
GSI	–	0.006	-0.001	–	0.040**	0.039**	–	0.053**	0.050**	–	0.041**	0.036**
		(0.009)	(0.009)		(0.009)	(0.009)		(0.009)	(0.009)		(0.009)	(0.009)
Distance	-0.025**	-0.025**	-0.025**	-0.025**	-0.024**	-0.025**	-0.024**	-0.024**	-0.024**	-0.023**	-0.024**	-0.024**
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Shipments	0.005^{+}	0.005^{+}	0.005^{+}	0.004	0.005^{+}	0.004	0.004	0.004	0.004	0.005^{+}	0.004	0.005^{+}
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Northeast	-0.049*	-0.048*	-0.049*	-0.015**	-0.050**	-0.051**	-0.050*	-0.050*	-0.050*	-0.052**	-0.051**	-0.052**
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.020)	(0.019)	(0.020)	(0.020)	(0.020)	(0.020)
Midwest	0.042**	0.042**	0.042**	0.045**	0.044**	0.045**	0.045**	0.045**	0.045**	0.045**	0.045**	0.045**
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
South	0.109**	0.109**	0.109**	0.109**	0.110**	0.109**	0.110**	0.111**	0.110**	0.113**	0.112**	0.113**
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.012)	(0.012)	(0.012)
West	-0.066**	-0.064**	-0.066**	-0.062**	-0.063**	-0.062**	-0.062**	-0.063**	-0.062**	-0.064**	-0.063**	-0.064**
	(0.015)	(0.015)	(0.015)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Adj. R-sq.	0.265	0.265	0.265	0.263	0.264	0.263	0.260	0.261	0.260	0.258	0.258	0.258
No of Obs.	113,713	114,143	113,713	111,830	112,260	111,830	109,859	110,289	109,859	107,888	108,318	107,888

Table 8.2: Secondary Panel Regressions (March 21, 2020 - May 1, 2021)

Robust standard errors in parentheses; $^{+}$ $p<0.1$, *: $p<0.05$, ** $p<0.01$.

Panel data regression results are presented in Table 8.2. We include up to 4 weekly lags of our key RHS variables, namely, COVID-19, average CMI and GSI. We group twelve columns into four based on the number of lags considered. The first three columns present the coefficient estimates for the one-week lagged variables of the COVID and ACMI, COVID and GSI and, COVID, ACMI and GSI together, respectively. The next three groups of columns present the results with the same sets of variables lagged two, three and four weeks, respectively.

As expected, the coefficient estimate for the log normalized new COVID-19 case ratio is positive for all lags. Even though with a value of 0.003, it is not statistically significant for the one-week case, it increases to 0.006 and eventually to 0.010 and becomes statistically significant as the number of lags is increased to two, three and four weeks. The use of ACMI and GSI variables in the specification does not affect the size and the statistical significance of the COVID-19 coefficient estimate. For the four-week lagged case, a 10 percent increase in the normalized COVID-19 cases in the source state relative to the target state would imply a 0.10 points increase in the connectedness from the source state's initial unemployment claims to the target state.

When the normalized COVID-19 cases increase in the source state relative to the target state, the regression results indicate increased unemployment spillovers from the source to the target state. This is consistent with the first-stage regression findings, where the higher normalized Covid-19 cases in a state lead to higher unemployment in that state. The resulting increase in unemployment may spill over to other states with lower Covid-19 cases and unemployment insurance claims.

Alternatively, we can refer to the strong evidence shown by Akovali and Yilmaz (2020) for the connectedness of COVID-19 cases across the U.S. states. Considering their findings, it is possible to claim that the spillover of the COVID-19 cases from the source to the target state effectively leads to the increase in unemployment claims in the target state taking place after the increase in the source state unemployment. The underlying basis for the spillover of initial unemployment claims between the source and target states, therefore, is the spillover of COVID-19 cases from the source to the target state.

This finding has a crucial public policy implication as it directly shows how increases in COVID-19 cases negatively affect the pairwise labor market outcomes. Yet, the coefficient estimate is quite small, equal to or less than 0.01, indicating minimal impact of the relative COVID-19 cases on the connectedness of the relative initial unemployment claims.

The coefficient estimates for all lags of the ACMI variable are negative, as expected, and with the exception of the two-weeks lag, they are statistically insignificant. The lagged ACMI coefficient estimates imply that as the community mobility decreases, social and economic activity would be curtailed in the source state, leading to increased unemployment. This will also be reflected in economic spillovers to other states leading to unemployment connectedness from the source to the target states. Furthermore, the size of the coefficient estimate indicates a more sizeable impact of the community mobility on unemployment connectedness than the COVID19 cases. In the first, third and fourth weekly lag estimations it varies between -0.119 and -0.194, indicating that a 10% decrease in ACMI in the source state relative to the target state would lead to a 1.2 to 1.9 points increase in the unemployment connectedness.

Except for the one-week lag, the sign of the relative GSI coefficient estimate is positive and statistically significant. The statistically significant GSI coefficient estimates vary between 0.036 and 0.053 depending on the number of weekly lags considered. A 10% tightening of the source state government's public health policies relative to the target state increases the unemployment connectedness from source to target state by 0.36 to 0.53 percentage points after two to four weeks. When the state government decision is made, this would be reflected in the GSI within within a few days, but its negative impact on social and economic activity and hence unemployment might not be felt immediately. As a result, its impact on unemployment connectedness from the source to the target state is observed only after two weeks.

In addition to these three variables directly related to the COVID-19 pandemic, our secondary panel regressions also include variables to measure the effect of geographic and economic linkages between the U.S. states on unemployment connectedness across the states. The first one of these is the distance variable that measures the geodesic distance between two states. The distance variable captures the cross-section variation in geographical location. The farther the two states are apart from each other, the lower would be the unemployment connectedness between them.

A coefficient estimate of -0.025 for the log distance variable implies that, holding everything else constant, the unemployment connectedness between a pair of states that are located 10% closer to each other than another pair would be 0.25 points higher compared to the other pair of states.

Another variable we use measures the domestic trade links between pairs of states.

The higher the share of shipments from target to the source state in total shipments to the source state, the stronger would be the demand linkages from the source to the target state and hence the higher would be the unemployment connectedness from the source to the target state.

As expected, distance has a negative impact on connectedness while the rate of shipments has a positive sign. Both of these variable have only the cross-section dimension and hence should be interpreted accordingly.

The coefficient estimate for the log shipment rate between the source and the target state is positive and varies between 0.004 and 0.005, but it is statistically significant at the 10% level. A 10% increase in the shipment ratio generates an increase of around 0.05 points increase in the unemployment connectedness. We think that the coefficient estimate is too small, perhaps because the distance variable captures an important variation in the economic relationship between pairs of states.

We finally discuss the coefficient estimates for the regional dummies. Using the US Census Bureau's four broad regional classifications (Northeast, Midwest, South and West), we define the regional source to target dummies. When both the source and target state are in the same region, the regional dummy takes a value of one. If they are in different regions, then the regional dummy takes a value of zero.

The coefficient estimates of the four source to target regional dummies are all statistically significant. The coefficient estimates for the Northeast and the West regional dummies are negative, indicating that the unemployment connectedness between pairs of states located in these two regions tends to have lower unemployment connectedness compared to the pairs of states where at least one state is located in other regions.

The coefficient estimates of the dummy variables for the South and Midwest regions are statistically significant and positive. The coefficient estimates imply that the unemployment connectedness tend to be stronger across the states in the South and Midwest regions. These states happen to be mostly states with Republican governors or Republican majority states. They differentiated themselves for being more relaxed vis-a-vis the COVID-19 pandemic and hence experienced the largest number of COVID-19 cases and connectedness among each other (see Akovali and Yilmaz (2020)).

BIBLIOGRAPHY

Acemoglu, D., Autor, D., Dorn, D., Hanson, G. H., and Price, B. (2016). Import competition and the great us employment sag of the 2000s. *Journal of Labor Economics*, 34(S1):S141–S198.

Akovali, U. and Yilmaz, K. (2020). Polarized Politics of Pandemic Response and the Covid-19 Connectedness Across the US States. *Covid Economics, Vetted and Real-time Papers*.

Alder, S., Lagakos, D., and Ohanian, L. (2014). Competitive pressure and the decline of the rust belt: A macroeconomic analysis. Technical report, National Bureau of Economic Research.

Amburgey, A. and Birinci, S. (2020). Which Earnings Groups Have Been Most Affected by the COVID-19 Crisis? *Available at SSRN 3658395*.

Autor, D. et al. (2010). The polarization of job opportunities in the us labor market: Implications for employment and earnings. *Center for American Progress and The Hamilton Project*, 6:11–19.

Autor, D. H., Katz, L. F., and Kearney, M. S. (2008). Trends in us wage inequality: Revising the revisionists. *The Review of economics and statistics*, 90(2):300–323.

Autor, D. H., Katz, L. F., and Krueger, A. B. (1998). Computing inequality: have computers changed the labor market? *The Quarterly journal of economics*, 113(4):1169–1213.

Bailey, M., Cao, R., Kuchler, T., Stroebel, J., and Wong, A. (2018). Social connectedness: Measurement, determinants, and effects. *Journal of Economic Perspectives*, 32(3):259–80.

Barnichon, R. and Figura, A. (2015). Labor market heterogeneity and the aggregate matching function. *American Economic Journal: Macroeconomics*, 7(4):222–49.

Bayer, P., Ferreira, F., and Ross, S. L. (2016). The vulnerability of minority homeowners in the housing boom and bust. *American Economic Journal: Economic Policy*, 8(1):1–27.

Birinci, S., Karahan, F., Mercan, Y., and See, K. (2020). Labor Market Policies during an Epidemic. *FRB St. Louis Working Paper*, (2020-024).

Blanchard, O. (2016). The phillips curve: Back to the'60s? *American Economic Review*, 106(5):31–34.

Borbely, J. M. (2009). Us labor market in 2008: economy in recession. *Monthly Lab. Rev.*, 132:3.

Bostanci, G. and Yilmaz, K. (2020). How connected is the global sovereign credit risk network? *Journal of Banking & Finance*, page 105761.

Burda, M. C. and Profit, S. (1996). Matching across space: Evidence on mobility in the Czech Republic. *Labour Economics*, 3(3):255–278.

Cajner, T., Crane, L. D., Decker, R. A., Grigsby, J., Hamins-Puertolas, A., Hurst, E., Kurz, C., and Yildirmaz, A. (2020). The US labor market during the beginning of the pandemic recession. Technical report, National Bureau of Economic Research.

Caliendo, L., Parro, F., Rossi-Hansberg, E., and Sarte, P.-D. (2018). The impact of regional and sectoral productivity changes on the us economy. *The Review of economic studies*, 85(4):2042–2096.

Choi, J., Kuziemko, I., Washington, E., and Wright, G. (2020). Local economic and political effects of trade deals: Evidence from nafta.

Coibion, O., Gorodnichenko, Y., and Weber, M. (2020). Labor markets during the covid-19 crisis: A preliminary view. Technical report, National Bureau of Economic Research.

Cunningham, E. (2018). Great recession, great recovery-trends from the current population survey. *Monthly Lab. Rev.*, 141:1.

Dao, M., Furceri, D., and Loungani, P. (2017). Regional labor market adjustment in the United States: trend and cycle. *Review of Economics and Statistics*, 99(2):243–257.

David, H. and Dorn, D. (2013). The growth of low-skill service jobs and the polarization of the us labor market. *American Economic Review*, 103(5):1553–97.

David, H., Dorn, D., and Hanson, G. H. (2013). The china syndrome: Local labor market effects of import competition in the united states. *American Economic Review*, 103(6):2121–68.

Deming, W. G. (1996). A decade of economic change and population shifts in us regions. *Monthly Lab. Rev.*, 119:3.

Demirer, M., Diebold, F., Liu, L., and Yilmaz, K. (2018). Estimating global bank network connectedness. *Journal of Applied Econometrics*, 33(1):1–15.

Derenoncourt, E. and Montialoux, C. (2021). Minimum wages and racial inequality. *The Quarterly Journal of Economics*, 136(1):169–228.

Di Caro, P. (2015). Recessions, recoveries and regional resilience: evidence on italy. *Cambridge Journal of Regions, Economy and Society*, 8(2):273–291.

Diebold, F. and Yilmaz, K. (2009). Measuring financial asset return and volatility spillovers, with application to global equity markets. *Economic Journal*, 119:158–171.

Diebold, F. and Yilmaz, K. (2012). Better to give than to receive: Predictive measurement of volatility spillovers. *International Journal of Forecasting*, 28:57–66.

Diebold, F. and Yilmaz, K. (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics*, 182:119–134.

Dingel, J. I. and Neiman, B. (2020). How many jobs can be done at home? Technical report, National Bureau of Economic Research.

Dippel, C., Gold, R., and Heblich, S. (2015). Globalization and its (dis-) content: Trade shocks and voting behavior. Technical report, National Bureau of Economic Research.

Dorn, D., Hanson, G., Majlesi, K., et al. (2020). Importing political polarization? the electoral consequences of rising trade exposure. *American Economic Review*, 110(10):3139–83.

Dube, A. and Lindner, A. (2021). City limits: What do local-area minimum wages do? *Journal of Economic Perspectives*, 35(1):27–50.

Elsby, M. W., Hobijn, B., and Sahin, A. (2010). The labor market in the Great Recession. Technical report, National Bureau of Economic Research.

Fahr, R. and Sunde, U. (2006). Spatial mobility and competition for jobs: Some theory and evidence for Western Germany. *Regional Science and Urban Economics*, 36(6):803–825.

Fairlie, R. W., Couch, K., and Xu, H. (2020). The impacts of covid-19 on minority unemployment: First evidence from april 2020 cps microdata. Technical report, National Bureau of Economic Research.

Farber, H. S. (2011). Job loss in the Great Recession: Historical perspective from the displaced workers survey, 1984-2010. Technical report, National Bureau of Economic Research.

Fedorets, A., Lottmann, F., and Stops, M. (2019). Job matching in connected regional and occupational labour markets. *Regional Studies*, 53(8):1085–1098.

Fishback, P. V. and Seltzer, A. J. (2021). The rise of american minimum wages, 1912–1968. *Journal of Economic Perspectives*, 35(1):73–96.

Ganong, P., Noel, P. J., and Vavra, J. S. (2020). Job matching in connected regional and occupational labour markets. Technical report, National Bureau of Economic Research.

Ganong, P. and Shoag, D. (2017). Why has regional income convergence in the us declined? *Journal of Urban Economics*, 102:76–90.

Gardner, J., Hipple, S., and Nardone, T. (1994). The labor market improves in 1993. *Monthly Lab. Rev.*, 117:3.

Gardner, J. M. (1994). The 1990-91 recession: how bad was the labor market. *Monthly Lab. Rev.*, 117:3.

Goolsbee, A. and Syverson, C. (2020). Fear, lockdown, and diversion: Comparing drivers of pandemic economic decline 2020. *Journal of Public Economics*, 193:104311.

Gupta, S., Montenovo, L., Nguyen, T. D., Rojas, F. L., Schmutte, I. M., Simon, K. I., Weinberg, B. A., and Wing, C. (2020). Effects of social distancing policy on labor market outcomes. Technical report, National Bureau of Economic Research.

Hall, R. E. and Kudlyak, M. (2020). Why has the us economy recovered so consistently from every recession in the past 70 years? *NBER Working Paper*, (w27234).

Hamilton, J. D. and Owyang, M. T. (2012). The propagation of regional recessions. *Review of Economics and Statistics*, 94(4):935–947.

Hazell, J., Herreno, J., Nakamura, E., and Steinsson, J. (2020). The slope of the phillips curve: evidence from us states. Technical report, National Bureau of Economic Research.

Hedin, T. J., Schnorr, G., and Von Wachter, T. (2020). An Analysis of Unemployment Insurance Claims in California During the COVID-19 Pandemic. *California Policy Lab policy brief.*

Higashi, Y. (2018). Spatial spillovers in job matching: Evidence from the Japanese local labor markets. *Journal of the Japanese and International Economies*, 50:1–15.

Holzer, H. J. and Hlavac, M. (2012). *A very uneven road: US labor markets in the past 30 years.* Institute for Research on Poverty, University of Wisconsin-Madison.

Hynninen, S.-M. (2005). Matching across space: evidence from Finland. *Labour*, 19(4):749–765.

Irwin, N. (2018). The most important least-noticed economic event of the decade. *New York Times.*

Jacomy, M., Heymann, S., Venturini, T., and Bastian, M. (2014). ForceAtlas2: A continuous graph layout algorithm for handy network visualization designed for the Gephi software. *PLoS ONE*, 9(6):e98679.

Kahn, L. B., Lange, F., and Wiczer, D. G. (2020). Labor Demand in the time of COVID-19: Evidence from vacancy postings and UI claims. Technical report, National Bureau of Economic Research.

Katz, L. F. and Murphy, K. M. (1992). Changes in relative wages, 1963–1987: supply and demand factors. *The quarterly journal of economics*, 107(1):35–78.

Kermack, W. and McKendrick, A. (1927). A Contribution to the Mathematical Theory of Epidemics. *Proceedings of the Royal Society of London. Series A, Containing Papers of a Mathematical and Physical Character*, 115(772):700–721.

Kline, P. and Moretti, E. (2013). Place based policies with unemployment. *American Economic Review*, 103(3):238–43.

Koop, G., Pesaran, M., and Potter, S. (1996). Impulse response analysis in nonlinear multivariate models. *Journal of Econometrics*, 74(1):119–147.

Krueger, A. B. and Solow, R. (2002). *The roaring nineties: can full employment be sustained?* Russell Sage Foundation.

Langdon, D. S., McMenamin, T. M., and Krolik, T. J. (2002). Us labor market in 2001: Economy enters a recession. *Monthly Lab. Rev.*, 125:3.

Lottmann, F. (2012). Spatial dependencies in German matching functions. *Regional Science and Urban Economics*, 42(1-2):27–41.

Malgouyres, C. (2017). Trade shocks and far-right voting: Evidence from french presidential elections. *Robert Schuman Centre for Advanced Studies Research Paper No. RSCAS*, 21.

Manning, A. and Petrongolo, B. (2017). How local are labor markets? Evidence from a spatial job search model. *American Economic Review*, 107(10):2877–2907.

Marinescu, I. E., Skandalis, D., and Zhao, D. (2020). Job search, job posting and unemployment insurance during the COVID-19 crisis. *Job Posting and Unemployment Insurance During the COVID-19 Crisis (July 30, 2020).*

Mian, A. and Sufi, A. (2014). What explains the 2007–2009 drop in employment? *Econometrica*, 82(6):2197–2223.

Mitman, K. and Rabinovich, S. (2020). Optimal unemployment benefits in the pandemic.

Montenovo, L., Jiang, X., Rojas, F. L., Schmutte, I. M., Simon, K. I., Weinberg, B. A., and Wing, C. (2020). Determinants of disparities in covid-19 job losses. Technical report, National Bureau of Economic Research.

Nadrone, T., Herz, D., Mellor, E., and Hipple, S. (1993). 1992: Job market in the doldrums. *Monthly Lab. Rev.*, 116:3.

Rappaport, J. (2012). Why does unemployment differ persistently across metro areas? *Economic Review-Federal Reserve Bank of Kansas City*, page 1.

Şahin, A., Song, J., Topa, G., and Violante, G. L. (2014). Mismatch unemployment. *American Economic Review*, 104(11):3529–64.

Tibshirani, R. (1996). Regression Shrinkage and Selection via the Lasso. *Journal of the Royal Statistical Society, Series B (Methodological)*, pages 267–288.

Wang, H. and Yamamoto, N. (2020). Using A Partial Differential Equation with Google Mobility Data to Predict COVID-19 in Arizona. *Mathematical Biosciences and Engineering*, 17.

Wilson, D. J. (2020). Weather, Social Distancing, and the Spread of COVID-19. *Covid Economics*, 35:257–299.

Yagan, D. (2019). Employment hysteresis from the great recession. *Journal of Political Economy*, 127(5):2505–2558.

Yashiv, E. (2007). US labor market dynamics revisited. *Scandinavian journal of Economics*, 109(4):779–806.